Blind Date: Network Initiation and Status Competitions in an Influencer Economy

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A FEW WORDS FIRST ABOUT MY RESEARCH INTERESTS…

My work is situated at the intersection of economic sociology and science and technology

And social networks have been prominent in economic sociology…

Hence my interest in social networks

I am currently running two research projects on social networks, together with my current and former PhD students

Today's presentation is one of these projects, which is more advanced

The other project is an investigation of vote delegation in DAOs (decentralized autonomous organizations)—who delegates their vote to whom, and to what effects

But let's talk first about today's topic…

LET'S PLAY THE FOLLOWING GAME…

Assume you are back to high school and you have a math test every month… you get your grade after each test, but you also want to compare with your classmates… (you don't know their grades)… **what do you do?**

You have a few options:

1. Reveal your grade to the entire class (but you run the risk of your classmates not telling you their grades)
2. Ask your classmates one by one (takes time, they might turn you down)
3. Contact some classmates and say, I will reveal you my grade if you reveal yours

Which option will you choose?

IF YOU HAVE CHOSEN OPTION #3, THEN..

You are playing **a Myerson game**

That is: you initiate a network in which, if the counterparty accepts, you reveal more information to each other

What is so interesting about Myerson games? Do you think they are only high school games?

A lot of digital platforms are variants of Myerson games

When you go on a date, you are playing a Myerson game

WHICH MEANS:

You initiate a tie in a network that depends on revealing information to each other

(We assume that the information is accurate and that the parties cannot lie. If the parties can lie, the game gets more complicated…)

Why is this interesting?

Going back to our initial high school game, we can ask:

Well, if I compare my grades with my classmates', will I perform better in math tests?

UNTIL NOW, WE HAVE TALKED ABOUT THE CONSEQUENCES OF NETWORK INITIATION…

And this is exactly our question today: what are the consequences of initiating a network and comparing performance on one's own performance?

Does initiating a network make me better at the game that I am playing? (dating, or math exams, etc.)

This is what we want to find out…

And, of course, we can make this question more complex, by asking for instance: what is a better strategy, to ask first or to wait to be asked by someone?

YOU HAVE NOTICED THAT UNTIL NOW I HAVEN'T TALKED MUCH ABOUT COMPUTATION, BUT ABOUT A VERY SPECIFIC QUESTION RELATED TO SOCIAL NETWORKS...

Why so?

Because we need to have first a question before we decide how to address it computationally or with other means (we can explore inductively too, but in this case, we do not take an inductive approach)

So, how do we go about this question: **does initiating a network make me better at the game I am playing (such as math tests)?**

WE ALSO WANT TO FIND A PLACE FOR THIS QUESTION WITHIN SOCIOLOGICAL DEBATES, BEFORE WE PROCEED WITH THE ANALYSIS…

Do we find such a place?

Yes, we do, with regard to social networks and status competitions (e.g., Gould, Burt, Podolny)

Status is related to perceived skill (in our example: math skill)

We find two camps:

1. **Actors of lower status tend to initiate ties with actors of higher status (I would like to connect to the math wizz kid in my class)**
2. **Tie initiation is a strategic device used to improve one's status (I don't really want to connect to the math wizz kid because that doesn't help my status at all)**

WHICH IS WHICH? OPTION #1 OR OPTION #2?

- Notice that until now we haven't addressed any computational issues at all, we have just prepared the ground on which we can intervene with computational means
- But now it is time to do so.
- What do we do? Well, we need first a dataset…
- And not any dataset, but one from a social network that competes on a specific dimension (such as math test grades)
- Do we have such a dataset? Yes, we do…

THE DATA

The dataset comes from a retail (individual) foreign exchange online social trading platform.

STPs are influencer economies specific to finance, integrating financial trading with social media. Participants form consensual, trading-centered social networks, communicating with each other, and seeing each other’s true financial performance in real time.

Our dataset comprises 3,522 active traders, with 51,866 link requests and 662,613 daily logs over a period of 18 months.

THE DATA

Fig. 1. Four possible outcomes of sending and receiving link requests

Trader A	Scenario	Trader B	Outcome
Sends request to Trader B	(1)	Accepts this request	Access to each other's trading histories and future trades
	(2)	Ignores this request	No access to each other's trading histories and future trades
	(3)	Rejects this request	No access to each other's trading histories and future trades
	(4)	Accepts this request But cancels it later	Access to each other's trading histories and future trades But the access is cut for both parties when link is canceled

THE DATA

Table 1. Summary of Friend Link Request by Month

Month	Friend link Request	Accepted	Accepted Rate	Pending	Declined	Canceled	Investors (cumulative)	Percent (cumulative)
Feb-09	18	14	77.78%	3	0	1	11	0.31%
Mar-09	195	132	67.69%	24	24	15	37	1.05%
Apr-09	392	269	68.62%	111	5	7	82	2.33%
May-09	674	449	66.62%	210	14	1	120	3.41%
Jun-09	352	226	64.20%	120	5	1	163	4.63%
Jul-09	450	277	61.56%	161	9	3	246	6.98%
Aug-09	1,049	630	60.06%	394	16	9	333	9.45%
Sep-09	1,714	992	57.88%	656	65	1	452	12.83%
Oct-09	4,219	2,474	58.64%	1,584	115	46	786	22.32%
Nov-09	4,672	2,301	49.25%	2,131	228	12	1,013	28.76%
Dec-09	3,125	1,603	51.30%	1,416	98	8	1,237	35.12%
Jan-10	3,308	1,929	58.31%	1,267	93	19	1,511	42.90%
Feb-10	4,520	2,273	50.29%	2,080	127	40	1,859	52.78%
Mar-10	6,347	2,561	40.35%	3,554	207	25	2,264	64.28%
Apr-10	10,032	3,544	35.33%	6,110	372	6	2,671	75.84%
May-10	6,013	2,137	35.54%	3,616	246	14	3,073	87.25%
Jun-10	4,786	1,393	29.11%	3,272	112	9	3,311	94.01%
Total	51,866	23,204	44.74%	26,709	1,736	217	3,311	94.01%

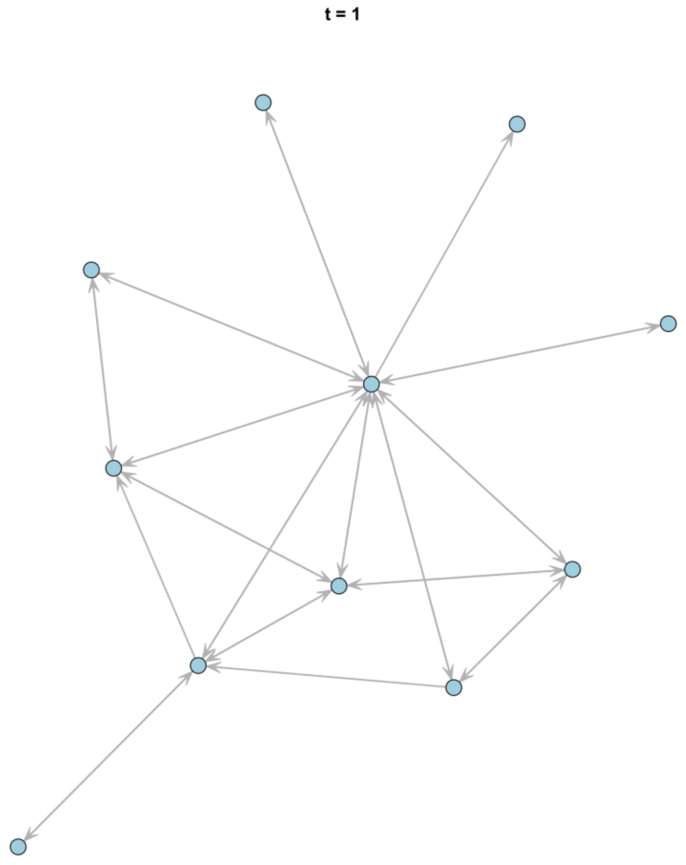
3. DATA

Table 2. Networks by Each Month

Month	Number of networks	Average size	Min size	Max size	S.D. of size
Feb-09	6	3.33	2	5	1.03
Mar-09	22	7.00	2	18	4.72
Apr-09	39	7.90	2	35	8.28
May-09	52	9.63	2	78	14.05
Jun-09	40	6.65	2	27	6.43
Jul-09	52	6.33	2	40	7.37
Aug-09	82	8.68	2	93	13.44
Sep-09	104	10.54	2	101	15.75
Oct-09	238	11.39	2	296	25.59
Nov-09	216	11.65	2	122	18.98
Dec-09	184	9.71	2	352	26.66
Jan-10	271	8.12	2	72	11.00
Feb-10	269	9.45	2	186	19.69
Mar-10	318	9.05	2	290	20.88
Apr-10	358	10.90	2	492	36.50
May-10	300	8.12	2	214	18.81
Jun-10	197	8.07	2	159	17.31

THE DATA

This is how our network evolves over 18 months…



METHODOLOGY

Temporal Exponential Random Graph Model (TERGM) (Leifeld, Cranmer and Desmarais, 2018)

1) The likelihood of two nodes (investors) tying depends upon attributes of nodes.

2) However, the probability of a tie forming between any two nodes is also impacted by the structure of the rest of the network (Cranmer and Desmarais, 2011) (cannot be measured by regression)

TERGM is uniquely tailored to capture inter-temporal dependencies in longitudinal networks. Its primary strength lies in reflecting how prior network configurations influence current network characteristics, a dynamic ill-suited for traditional regression.

TERGM

TERGM can detect both exogenous and endogenous dependencies.

Exogenous factors are external influences on network dynamics, including:

- Node attributes: Performance and behaviours (time-varying)
- Edge covariates: Assets preference, country and age (consistent)

Endogenous factors are the inherent network structure:

- reciprocity and other network structural properties, edges, mutual, or triple, etc.

TERGM (DATA)

The R package we utilized is the 'btergm package', which uses the bootstrapped pseudolikelihood inference methods (Desmarais and Cranmer, 2012) and generates the confidence interval for estimates.

For example:

Model1 <- btergm (mc_list ~ edges + mutual+ ttriple + nodeicov(“X1”) + …+ nodeicov(“Xn”) + edgecov(“Y1”) + … + edgecov(“Yn”), R = 1000)

Where:

1. “*mc_list*” is the networks, which can be defined with sent link requests or accepted link requests.

So that we can test the what factors influence the link request sent or accepted respectively.

2. “X1” and “Y1” represent the node attributes or edge covariates respectively.

3. Links have directions, which allows us to detect attributes for senders and recipients by “nodeocov” (o for out) and “nodeicov” (i for in).

TERGM (DATA)

The dataset comes from a retail (individual) foreign exchange online social trading platform.

- We only consider active accounts and merge the accounts held by the same investors in the dataset, by which we get 3522 traders.

- Even the first trade is on January 1st, 2009. The social connection was first established on February 18th, 2009, which is the 8th week of this year. Also, only three business days recorded in the last week, 28th, 29th, and 30th, of June 2010. ➔ The first seven weeks and the last week are excluded.

- So, we get 71 weeks/17 months/6 quarters, which are available for our TERGM model.

METHODOLOGY

We examine the impact of the network formed at time “t” on investors' performance and behaviors at time “t+1” from three perspectives:

- Performance (the average return during each time interval--week, month, or quarter)

$$R_{t+1} = \alpha + \beta_1 \cdot B_{t-1} + \beta_2 \cdot Ls_t + \beta_3 \cdot (B_{t-1} \times Ls_t) + \beta_4 \cdot X_t + \varepsilon_t$$

- Trading frequency(the average daily closed trades)

$$F_{t+1} = \alpha + \beta_1 \cdot B_{t-1} + \beta_2 \cdot Ls_t + \beta_3 \cdot (B_{t-1} \times Ls_t) + \beta_4 \cdot X_t + \varepsilon_t$$

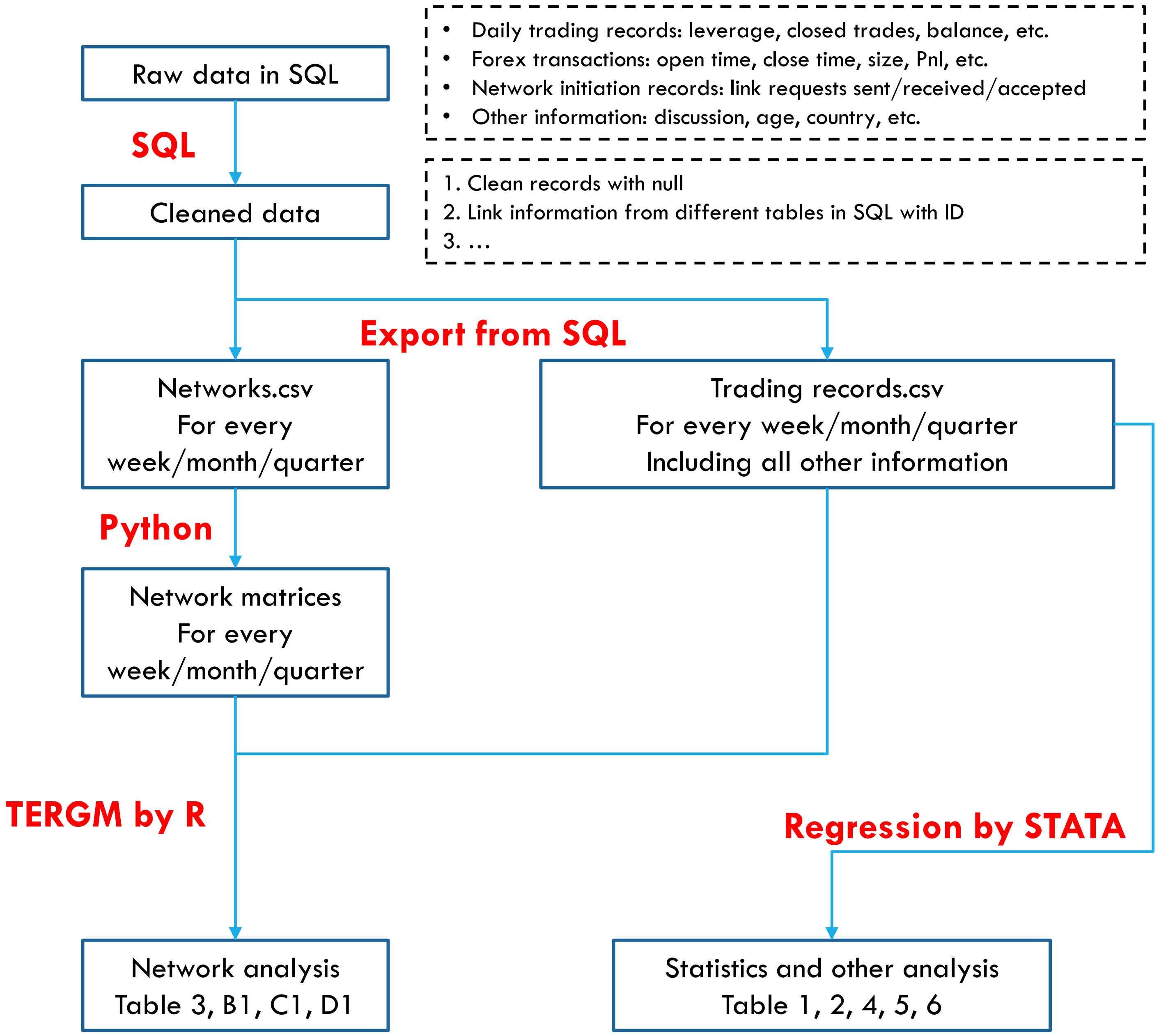
- Asset selection (based on the Herfindahl-Hirschman Index--HHI, we measure asset concentration in a way similar to measuring market concentration)

$$As_{t+1} = \alpha + \beta_1 \cdot B_{t-1} + \beta_2 \cdot Ls_t + \beta_3 \cdot (B_{t-1} \times Ls_t) + \beta_4 \cdot X_t + \varepsilon_t$$

Substitute Ls_t (link sent) by La_t (link accepted) and $L\boldsymbol{r}_t$ (link received); B_{t-1} (better performance) and W_{t-1} (worse performance)

There are four big steps:

1. Clean the data in SQL and export tables
2. Reformat the networks.csv into matrices using Python
3. Run the TERGM using R with network matrices and trading records
4. Summarize the statistics and sum the regressions using STATA



RESULTS

Table 3. Link Requests by Month by TERGM

We employ the TERGM to investigate whether the desire to compare triggers investors to form social networks initially. The primary variables encompass various combinations of returns, while the control variables account for node attributes, edge covariates, and fundamental network characteristics. Our primary focus is on the 'Better Return' and 'Worse Return' compared to previous periods; both are treated as dummy variables. Panel A and Panel B respectively present the influence of these factors on link request sent and received. *, **, *** means coefficients are in 90%, 95%, 99% confidence interval without zero inside respectively. (Bootstrapping sample size: 1000)

Panel A. Link Sent			(1)	(2)	(3)	(4)	(5)	(6)	(7)
Primary Variables		Better return	0.725***		1.062***	1.062***	1.059***	1.067***	1.064***
		Worse return		0.800***	1.133***	1.133***	1.130***	1.133***	1.130***
		Return				0.000	-0.002	0.000	-0.002
		Max daily return					0.021		0.022
		Min daily return					0.003		0.003
		Max transaction return						0.000	0.000
		Min transaction return						0.000	0.000
Control Factors	Node Attributes	Leverage	Yes	Yes	Yes	Yes	Yes	Yes	Yes
		Trading frequency	Yes	Yes	Yes	Yes	Yes	Yes	Yes
		Balance	Yes	Yes	Yes	Yes	Yes	Yes	Yes
		Net deposit	Yes	Yes	Yes	Yes	Yes	Yes	Yes
		Discussion	0.249***	0.255***	0.224***	0.224***	0.225***	0.228***	0.230***
		Reply	1.123***	1.124***	1.101***	1.101***	1.100***	1.096***	1.095***
		Likes	0.931***	0.917***	0.875***	0.875***	0.873***	0.877***	0.876***
		Avatar	0.003	0.008	-0.008	-0.008	-0.007	-0.007	-0.006
		Leader	0.104	0.129	-0.007	-0.007	-0.005	-0.005	-0.003
		Mobility	0.825***	0.840***	0.641***	0.641***	0.641***	0.640***	0.641***
	Edge Covariates	Same main pair	0.049***	0.050***	0.045***	0.045***	0.045***	0.046***	0.046***
		Country	0.340***	0.340***	0.355***	0.355***	0.355***	0.353***	0.353***
		Age (3)	-0.109***	-0.108***	-0.113***	-0.113***	-0.113***	-0.112***	-0.112***
	Network Basics	Edges	-9.385***	-9.410***	-9.450***	-9.450***	-9.450***	-9.449***	-9.450***
		Mutual	8.844***	8.863***	8.755***	8.755***	8.756***	8.756***	8.756***

RESULTS

Table 3. Link Requests by Month by TERGM (Continued)

Panel B. Link Received			(1)	(2)	(3)	(4)	(5)	(6)	(7)
Primary Variables		Better return	0.463***		0.634***	0.634***	0.634***	0.634***	0.634***
		Worse return		0.312***	0.532***	0.532***	0.533***	0.534***	0.535***
		Return				0.000	0.001	0.000	0.001
		Max daily return					-0.005		-0.005
		Min daily return					-0.001		-0.001
		Max transaction return						0.000	0.000
		Min transaction return						0.000	0.000
Control Factors	Node Attributes	Leverage	Yes	Yes	Yes	Yes	Yes	Yes	Yes
		Trading frequency	Yes	Yes	Yes	Yes	Yes	Yes	Yes
		Balance	Yes	Yes	Yes	Yes	Yes	Yes	Yes
		Net deposit	Yes	Yes	Yes	Yes	Yes	Yes	Yes
		Discussion	0.344***	0.366***	0.343***	0.343***	0.342***	0.340***	0.340***
		Reply	-0.171***	-0.172***	-0.195***	-0.195***	-0.195***	-0.192***	-0.192***
		Likes	-0.197***	-0.206***	-0.225***	-0.225***	-0.225***	-0.227***	-0.226***
		Avatar	0.216***	0.219***	0.215***	0.215***	0.215***	0.214***	0.214***
		Leader	-0.314***	-0.290***	-0.389***	-0.389***	-0.389***	-0.390***	-0.390***
		Mobility	-0.947***	-0.935***	-0.977***	-0.977***	-0.977***	-0.977***	-0.977***
	Edge Covariates	Same main pair	0.042***	0.043***	0.040***	0.040***	0.040***	0.039**	0.039**
		Country	0.341***	0.340***	0.345***	0.345***	0.345***	0.347***	0.347***
		Age (3)	-0.107***	-0.106***	-0.108***	-0.108***	-0.108***	-0.108***	-0.108***
	Network Basics	Edges	-7.040***	-7.026***	-7.106***	-7.106***	-7.106***	-7.106***	-7.106***
		Mutual	8.841***	8.859***	8.756***	8.756***	8.756***	8.757***	8.757***

RESULTS

Table 4. Whose Friend Link Requests Will Be Accepted and Maintained

In the light of status competition, we define dependent variables to denote whether recipients have a higher return, leverage, trading frequency and balance compared to senders (marked as sR_Performance, sR_Leverage, sR_Trading frequency, and sR_Balance). Subsequently, we investigate whether these factors influence the acceptance and continuation of online friendships, as demonstrated by models (1) to (4). The variables to denote whether senders have a higher return, leverage, trading frequency and balance compared to recipients are marked as Sr_Performance, Sr_Leverage, Sr_Trading frequency, and Sr_Balance respectively. The control variables are deposit, communication, mobility, same main pair, country, age. Standard errors in parentheses are clustered at individual level and ***, **, and * denote significance at $p < 0.01$, $p < 0.05$, and $p < 0.1$, respectively.

	Panel A1: Link Accepted				Panel A2: Link Canceled			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
sR_Performance	0.024***	0.022***	0.023***	0.021***	-0.002**	-0.002**	-0.002**	-0.002**
	(0.005)	(0.005)	(0.005)	(0.005)	(0.001)	(0.001)	(0.001)	(0.001)
sR_Leverage	0.078***			0.053***	-0.001			0.000
	(0.007)			(0.008)	(0.001)			(0.001)
sR_Trading frequency		0.075***		0.035***		-0.001		-0.001
		(0.008)		(0.008)		(0.001)		(0.001)
sR_Balance			0.046***	0.032***			-0.001	0.000
			(0.007)	(0.007)			(0.001)	(0.001)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time and Individual FE.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	51,728	51,728	51,728	51,728	51,728	51,728	51,728	51,728
R^2	0.614	0.614	0.612	0.615	0.077	0.077	0.077	0.077

	Panel B1: Link Accepted				Panel B2: Link Canceled			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Sr_Performance	0.012**	0.013**	0.012**	0.016***	0.002**	0.001**	0.002**	0.001**
	(0.005)	(0.005)	(0.005)	(0.005)	(0.001)	(0.001)	(0.001)	(0.001)
Sr_Leverage	-0.034***			-0.021***	0.000			0.000
	(0.006)			(0.007)	(0.001)			(0.001)
Sr_Trading frequency		-0.033***		-0.011		0.000		0.000
		(0.006)		(0.007)		(0.001)		(0.001)
Sr_Balance			-0.040***	-0.033***			0.000	0.000
			(0.007)	(0.007)			(0.001)	(0.001)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time and Individual FE.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	51,728	51,728	51,728	51,728	51,728	51,728	51,728	51,728
R^2	0.611	0.611	0.611	0.612	0.077	0.077	0.077	0.077

RESULTS

Table 5. Link Requests and Ranking in the Networks by Month

We test whether the rankings of investors' performance (compared with their linked online peers) in their contemporary networks will affect their link requests send out and received in. The ranking is defined as the orders from high to low, which means a small number ranking is better, e.g., a smaller ranking of performance means a higher return. We show the results for three time intervals, week, month and quarter, by Panel A, Panel B and Panel C respectively. The significant and positive coefficients of the rankings on link sent across Panel A, B and C mean a low status of investors in their current networks will lead them seek new connections more actively. However, they are also more welcomed by others, evident by the significant and positive coefficients for link received. Standard errors in parentheses are clustered at individual level and ***, **, and * denote significance at p < 0.01, p < 0.05, and p < 0.1, respectively.

	Panel A: Week		Panel B: Month		Panel C: Quarter	
	Link sent	Link received	Link sent	Link received	Link sent	Link received
Ranking	0.007** (0.003)	0.013*** (0.003)	0.029*** (0.011)	0.056*** (0.013)	0.145*** (0.036)	0.180*** (0.046)
Link sent		0.084*** (0.014)		0.143*** (0.023)		0.128*** (0.033)
Link received	0.115*** (0.012)		0.135*** (0.018)		0.086*** (0.023)	
Pending	1.329*** (0.072)	-0.099*** (0.018)	1.324*** (0.064)	-0.175*** (0.029)	1.350*** (0.056)	-0.162*** (0.044)
Declined	1.124 (0.871)	-0.127* (0.071)	1.488* (0.898)	-0.190 (0.121)	1.231 (0.868)	-0.143 (0.175)
Withdrawn	2.180*** (0.201)	0.145 (0.117)	3.160*** (0.442)	-0.106 (0.167)	3.308*** (0.574)	0.143 (0.257)
Leverage	Yes	Yes	Yes	Yes	Yes	Yes
Balance	Yes	Yes	Yes	Yes	Yes	Yes
Net deposit	Yes	Yes	Yes	Yes	Yes	Yes
Communication	Yes	Yes	Yes	Yes	Yes	Yes
Mobility	Yes	Yes	Yes	Yes	Yes	Yes
Age	Yes	Yes	Yes	Yes	Yes	Yes
Month FE.	Yes	Yes	Yes	Yes	Yes	Yes
Individual FE.	Yes	Yes	Yes	Yes	Yes	Yes
N	220,358	220,358	56,287	56,287	19,866	19,866
R^2	0.975	0.130	0.979	0.271	0.984	0.420

RESULTS

Table 6. The Impact of Established Social Networks on Investor Performance and Behaviors by Month

This table presents results examining the extent to which investor performance and behaviors at time "t+1" are influenced by friend link requests at time "t". In the preceding section, we established that friend link requests at time "t" correlate with the Better and Worse returns at time "t-1". Consequently, we evaluate the effects of both Ls_t (link sent) and La_t (link accepted), as well as B_{t-1} and W_{t-1}. This gives rise to four variable combinations: link sent & better performance, link sent & worse performance, link accepted & better performance, and link accepted & worse performance. Beyond the fundamental control variables, we also integrate market factors. These encompass the carry factor, momentum factor, value factor, and volatility factor, which are considered emblematic of various trading strategies employed by currency traders, as suggested by Pojarliev and Levich (2008). Standard errors in parentheses are clustered at individual level and ***, **, and * denote significance at p < 0.01, p < 0.05, and p < 0.1, respectively.

	Panel A: Performance (t+1)				Panel B: Trading frequency (t+1)				Panel C: Asset selection (t+1)			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
$B_{t-1} \times Ls_t$	0.004* (0.002)				-0.013*** (0.004)				-0.036* (0.019)			
$W_{t-1} \times Ls_t$		-0.001 (0.001)				-0.004 (0.003)				-0.013 (0.013)		
$B_{t-1} \times La_t$			0.017* (0.009)				-0.052*** (0.013)				-0.189*** (0.064)	
$W_{t-1} \times La_t$				-0.004 (0.004)				-0.025** (0.013)				-0.056 (0.043)
B_{t-1}	-1.778*** (0.494)		-1.786*** (0.498)		3.375*** (0.145)		3.396*** (0.146)		9.022*** (0.282)		9.123*** (0.284)	
W_{t-1}		0.795*** (0.196)		0.797*** (0.198)		1.993*** (0.255)		2.011*** (0.257)		14.511*** (0.316)		14.542*** (0.319)
Ls_t	0.001 (0.002)	-0.007* (0.004)			-0.019 (0.014)	-0.029** (0.014)			0.386*** (0.063)	0.301*** (0.052)		
La_t			-0.004 (0.005)	-0.005 (0.003)			-0.003 (0.015)	-0.020 (0.013)			0.452*** (0.071)	0.321*** (0.060)
Received	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pending	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Declined	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Canceled	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Leverage	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Balance	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Net deposit	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Communication	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Mobility	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Age	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Market factors	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month FE.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual FE.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	59,874	59,874	59,874	59,874	59,874	59,874	59,874	59,874	59,874	59,874	59,874	59,874
R^2	0.046	0.045	0.046	0.045	0.150	0.137	0.150	0.137	0.369	0.409	0.370	0.409

FINDINGS

1. Actors are more likely to initiate networks after a a change in performance (compared with the previous period).
2. They tend to accept and maintain link requests with others who perform worse than them. (Against hypothesis 1, slide 8)
3. After having initiating networks, actors make efforts to show better performance relative to others in their network. (One improves for one's audience.)
4. Actors who are low status in current networks seek new connections more actively.
5. Over time, informal networks evolve; high-status participants tend to grant access to information within their networks, but also to exclude others from joining, while low-status ones keep seeking new networks.

CONCLUSION

We argue:

1. Network initiation is used as a strategic device in status competitions.
2. Actors seek to maintain or improve their status and seek ties with those who perform lower.
3. High status actors tend to exclude other high status actors from their networks.
4. Performance improves unequally for actors who send out ties and actors who wait to receive ties, respectively.

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Thank you!