

# Informative Social Interactions

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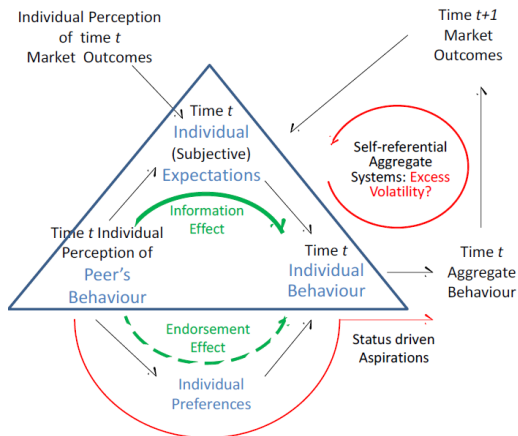
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# Question and Motivation

- *Do social interactions matter for financial behaviour? i.e.*
  - Is it what others' **know** or what others' **do**?
  - How does **information from others** about the stock market affect own stock holding decisions?
  - How does stock market **participation of others** influence own stock holding decisions?
  - What do people get out of social interactions?
- Why do we care?
  - 2008 subprime mortgage crisis: Is there a role for **social interactions** in the spread of (*poor*) financial behavior?
  - Important for (i) efficient dissemination of information on financial products/assets, (ii) designing and regulating successful/'fashionable' on-line investment clubs, and (iii) overcoming financial literacy limitations in the population, potentially responsible for (iv) booms and busts in asset markets,
  - ex. 'Excess volatility puzzle': Do **social interactions** contribute? How?

# What do We Do

We design and collect novel primary data, and find that **social interactions** affect individual stock market decisions by being **informative**:



## Strands of literature:

- 1 Literature on social interactions/peer effects on asset and debt behavior of households, ex. Hong, Kubik and Stein (2004), Georgarakos, Haliassos and Pasini (2014).
- 2 Literature on the effects of social imitation and influence on financial behavior:
  - Banerjee, Chandrasekhar, Duflo and Jackson (2013): identify a pure information effect (new financial product, microfinance in India)
  - Bursztyn, Ederer, Ferman and Yuchtman (2014): identify both information and endorsement/social utility effects (experiment with new financial product amongst brokerage account holders in Brazil)
  - Burnside, Eichenbaum and Rebelo (2016) and Bailey, Cao, Kuchler and Stroebel (2016): model, calibrate and identify a social interactions effect on housing in the US, respectively.

*Our contribution:* complementary, but for a representative sample of the population of a developed country, and about a traditional financial opportunity (stock market).

# What do people get out of social interactions?

**Information**



*Pure augmenting  
of investor's  
information set  
(Learning)*

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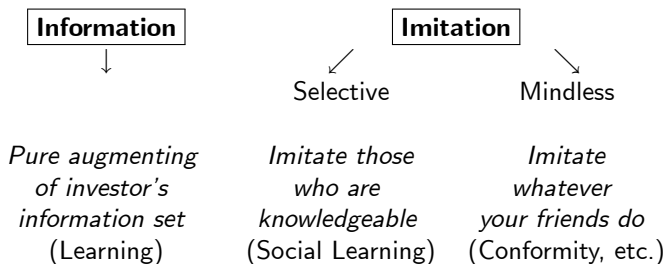
**Imitation**



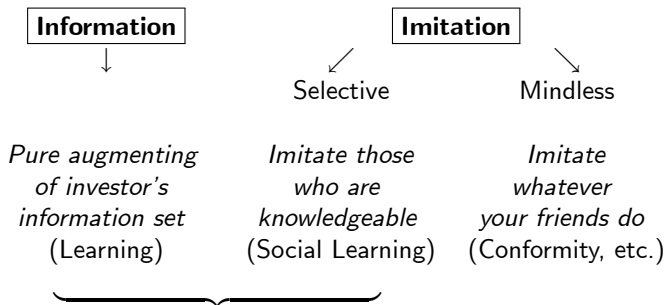
Mindless

*Imitate  
whatever  
your friends do  
(Conformity, etc.)*

# What do people get out of social interactions?



# What do people get out of social interactions?



## Informative social interactions



# Background for the model

- Within Hellwig (1980),
  - Static asset pricing model with a risky and a riskless asset, where asset prices transmit information;
  - Large number of heterogeneous agents with individual private signals on risky asset payoff (stocks);
- Ozsoylev and Walden (2011) embed an information network,
  - Network connections are exogenous;
  - Agents pool information by averaging signals from others they are 'connected to';
  - Agents form expectations about the net excess return on the basis of 'pooled signals' and prices;
  - *No 'social utility' motive* (conformity, etc.): within EU(.);
- We extend Ozsoylev and Walden (2011) to:
  - Heterogeneity in signal precision and risk preferences;
  - Agents 'pooled information' is **weighted** by the precisions of connections' signals;

# MODEL (I)

- Large discrete number of agents  $n$
- Two assets, one risky (stock) and one riskless (bond)
- The payoff of the riskless asset is 1
- The payoff of the risky asset follows a normal distribution  $X \sim N(\bar{X}, \sigma^2)$  and its price is  $p$
- Supply of stocks is random and is given by  $Z_n = nZ$ , where  $Z \sim N(\bar{Z}, \Delta^2)$  and  $\bar{Z} > 0$

- Agents have CARA preferences over final wealth  $\omega_i$  and solve

$$\max_{D_i} \mathbb{E} [-e^{-\rho_i \omega_i} | \mathcal{I}_i]$$

$$s.t. \omega_i = \omega_{0i} + D_i(X - p)$$

- To find the optimal demand  $D_i^*$  that maximizes expected utility, given their information set  $\mathcal{I}_i$

$$D_i^* = \frac{1}{\rho_i} \frac{\mathbb{E} [(X - p) | \mathcal{I}_i]}{\text{Var} [X | \mathcal{I}_i]}$$

# MODEL (II)

## Investors' information

- What is contained in  $\mathcal{I}_i$ ?
- Price  $p$  and signals
- Each agent observes an individual, private signal about the return on the risky asset  $y_i = X + \epsilon_i$ ,  $\epsilon_i \sim N(0, s_i^2)$
- Two networks:
  - 1 Acquaintances: adjacency matrix  $A$ , with  $a_{ij} \in \{0, 1\}$
  - 2 Information network: adjacency matrix  $G$ , with  $g_{ij} = a_{ij}/s_j^2$ , where  $s_j^{-2}$  is signal precision of agent  $j$
- The pooled payoff signal is

$$x_i = \frac{\sum_{k=1}^n g_{ik} y_k}{\sum_{k=1}^n g_{ik}} = X + \frac{\sum_{k=1}^n g_{ik} \epsilon_k}{\sum_{k=1}^n g_{ik}}$$

- Because  $n$  is large, no incentives to hide information (private signals) from one's friends

# MODEL (III)

## Main result

- Let the *connectedness* of investor  $i$  be

$$(1) \quad k_i = \sum_{k=1}^n \frac{a_{ik}}{s_k^2}$$

- Let the average connectedness of the information network be

$$\lim_{n \rightarrow \infty} \frac{1}{n} \sum_{i=1}^n \frac{k_i}{\rho_i} = \beta + o(1), \quad \beta < \infty$$

- Under reasonable/interpretable assumptions, as  $n \rightarrow \infty$ , there exists a NREE price  $p$  for the risky asset, which depends on average network connectedness  $\beta$

# Main Predictions of the Model

- In a large anonymous financial market, agents with more/better informed connections ( $k_i^*$ ):
  - 1 Form expectations of returns that give more weight to connections' signals ( $i$ 's pooled signal  $x_i$ ),

$$\mathbb{E}(X|\mathcal{I}_i) = \frac{k_i^* \sigma^2 \Delta^2}{k_i^* \sigma^2 \Delta^2 + \Delta^2 + \sigma^2 \beta^2} x_i + \left( \frac{\sigma^2 \beta^2 + \Delta^2}{k_i^* \sigma^2 \Delta^2 + \Delta^2 + \sigma^2 \beta^2} \right) \bar{X}$$

- 2 Invest a higher proportion of their financial wealth in risky assets (i.e. trade more aggressively),

$$D_i^* \equiv \frac{1}{\rho_i} \left[ \hat{\rho} \left( \frac{\bar{X} \Delta^2 + \bar{Z} \beta \sigma^2}{\hat{\rho} \sigma^2 \Delta^2 + \sigma^2 \beta} \right) - \hat{\rho} \left( \frac{\Delta^2}{\sigma^2 (\hat{\rho} \Delta^2 + \beta)} \right) \rho + k_i^* (x_i - \rho) \right]$$

# Survey design

- Survey designed to look for information effect of social interactions on stock market participation (demand);
- Part of ongoing survey on a representative sample of the French population by age and asset classes (PAT€R);
- Two questionnaires (TNS2014 and follow-up TNS2015), sent to 4,000 households: Unit responses to TNS2014 = 3,670. Of those, unit responses to TNS2015 = 2,587 (70.5% response rate);
- Questions on:
  - Respondent's risk preferences, and socio-economic and demographic characteristics;
  - Financial wealth (total and % invested in the stock market);
  - Perceptions and expectations about stock market returns (CAC-40) elicited probabilistically (Manski, 2004);
  - Detailed questionnaire for measures of individual connectedness, information and participation of peers;

# Separating social from financial circle

**C1:** *Approximately how many people are there in your social circle of acquaintances?*

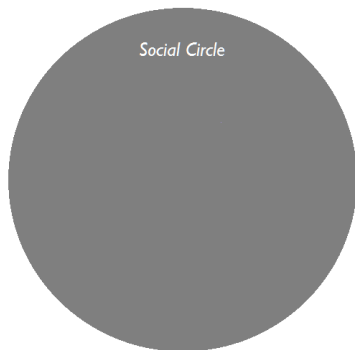
**D1:** *With how many people from your social circle (as identified in C1) do you interact with regarding your financial/investment matters?*

**C7i/D16i:** *In your opinion, what is the proportion of people in your social/financial circle that invests in the stock market? (as a %)*

**C7ii/D16ii:** *In your opinion, what is the proportion of people in your social/financial circle that is informed about the stock market? (as a %)*

# Proxy for connectedness: Social circle

*'Approximately how many people are there in your social circle of acquaintances?'*

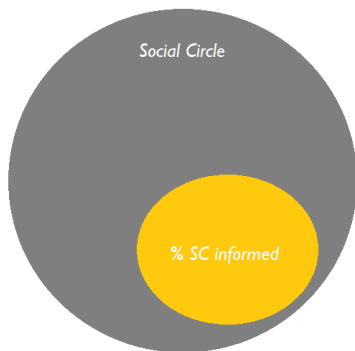


(Average: 53 approx.)



## Proxy for connectedness: Social circle

*'In your opinion, what is the proportion of people in your social circle that is informed about/follows the stock market?'*



(Average: 13% approx.)

# Do social interactions influence expectations of returns?

- OLS Econometric specification:

$$\text{Expec. } R_i = \kappa_0 + \underset{(+)}{\kappa_1 k_i^*} + \underset{(+)}{\kappa_2 D_i^e} + \kappa_3 \text{Perc. } R_i + \kappa_4 \rho_i + \kappa \tau_i + w_i$$

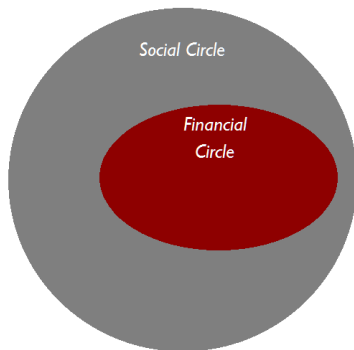
- Proxies for 'connectedness'  $k_i^*$  : %SC Inform, %FC Inform, %OC Inform
- (Proxies for 'imitation'  $D_i^e$  : %SC Particip, %FC Particip, %OC Particip)
- Risk aversion: CARA coefficient  $\rho_i$
- Perceptions about (3-year cumulative) stock market returns:  $\text{Perc. } R_i$
- Vector of individual characteristics,  $\tau_i$  : Age, gender, marital status, No. of children at home, education, geographical region of residence, employment status, borrowing constraints, quartiles for total wealth, income and (last 12-month) saving.

# Social interactions via expectations: Information

	Expec R	Expec R
% SC Inform.	0.000307 (0.000202)	
RA	-0.000708* (0.000382)	
Controls	Yes	
Constant	0.0405** (0.0170)	
<i>F</i>	2.805	
<i>R</i> <sup>2</sup>	0.034	
Observations	2,535	2,535

# Proxy for connectedness: Financial circle

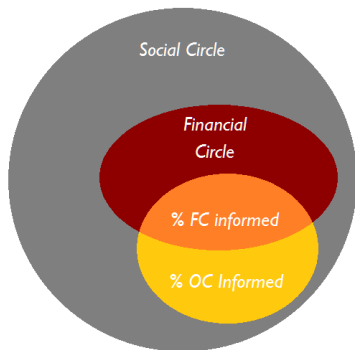
*'With how many people from your social circle do you interact with regarding your financial/investment matters?'*



(Average: 3 approx.)

# Proxy for connectedness: Financial circle

*'In your opinion, what is the proportion of people in your financial circle that follows the stock market?'*



(Average: 22% approx.)

# Social interactions via expectations: Information

	Expec R	Expec R
% SC Inform.	0.000307 (0.000202)	
% FC Inform.		0.000301** (0.000118)
% OC Inform.		-4.32e-05 (0.000191)
RA	-0.000708* (0.000382)	-0.000674* (0.000385)
Controls	Yes	Yes
Constant	0.0405** (0.0170)	0.0429** (0.0173)
<i>F</i>	2.805	3.075
<i>R</i> <sup>2</sup>	0.034	0.037
Observations	2,535	2,535

# Directly informative social interactions

- Tobit/Probit econometric specification:

$$D_i \equiv \%FW_i = \max\{0, \lambda_0 + \lambda_1 k_i^* + \lambda_2 \text{Expec. } R_i + \lambda_3 \rho_i (+\lambda_4 D_i^e) + \lambda \tau_i + u_i\}$$

(+)

- Proxies for  $k_i^*$ : %SC Inform, %FC Inform, %OC Inform
- (Proxies for  $D_i^e$ : %SC Particip, %FC Particip, %OC Particip)
- Expected (cumulative 5-year-ahead stock market) returns: *Expec.  $R_i$*
- Vector of individual characteristics,  $\tau_i$ : Age, gender, marital status, No. of children at home, education, region of residence, employment status, borrowing constraints, quartiles of total wealth, income, and liquid savings

# Pure information

	Pr(Stock)>0	% FW	Pr(Stock)>0	%FW
% SC Inform.	0.00943*** (0.00313)	0.234** (0.0973)		
% FC Inform.				
% OC Inform.				
Expec R	0.770** (0.321)	35.20*** (11.54)		
RA	-0.0140** (0.00626)	-0.366* (0.192)		
Controls	Yes	Yes		
Constant	-1.107*** (0.296)	-37.53*** (9.264)		
Log-likelihood	-1214	-3637		
LR $\chi^2$ (p-value)	401.7	370.3		
Pseudo $R^2$	0.160	0.0484		
Observations	2,525	2,294	2,525	2,294

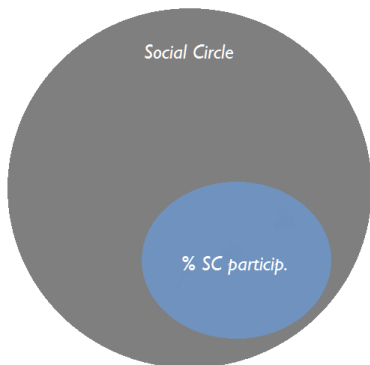


# Pure information

	Pr(Stock)>0	% FW	Pr(Stock)>0	%FW
% SC Inform.	0.00943*** (0.00313)	0.234** (0.0973)		
% FC Inform.			0.00844*** (0.00177)	0.142** (0.0575)
% OC Inform.			0.00126 (0.00317)	0.00784 (0.100)
Expec R	0.770** (0.321)	35.20*** (11.54)	0.680** (0.320)	33.40*** (11.52)
RA	-0.0140** (0.00626)	-0.366* (0.192)	-0.0137** (0.00624)	-0.380** (0.191)
Controls	Yes	Yes	Yes	Yes
Constant	-1.107*** (0.296)	-37.53*** (9.264)	-1.119*** (0.302)	-35.36*** (9.331)
Log-likelihood	-1214	-3637	-1202	-3634
LR $\chi^2$ (p-value)	401.7	370.3	435.4	376.3
Pseudo $R^2$	0.160	0.0484	0.168	0.0492
Observations	2,525	2,294	2,525	2,294

# Selective imitation

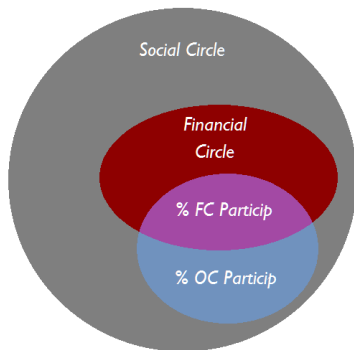
Repeat analysis but asking survey questions regarding the **participation** of acquaintances in the stock market...



## Selective imitation: Financial circle

... separating those with whom the respondent exchanges on financial matters (Fin. Circle) from those with whom s/he does not (Outer Circle):

*'In your opinion, what is the proportion of people in your financial circle that invests in the stock market?'*



# Social interactions via expectations: Selective Imitation

	Expec R	Expec R
% SC Particip.	0.000394 (0.000264)	
RA	-0.000702* (0.000383)	
Controls	Yes	
Constant	0.0418** (0.0170)	
<i>F</i>	2.792	
<i>R</i> <sup>2</sup>	0.034	
Observations	2,535	2,535

# Social interactions via expectations: (Selective) Imitation

	Expec R	Expec R
% SC Particip.	0.000394 (0.000264)	
% FC Particip.		0.000299*** (0.000115)
% OC Particip.		-2.16e-05 (0.000254)
RA	-0.000702* (0.000383)	-0.000684* (0.000385)
Controls	Yes	Yes
Constant	0.0418** (0.0170)	0.0437** (0.0170)
<i>F</i>	2.792	3.106
<i>R</i> <sup>2</sup>	0.034	0.037
Observations	2,535	2,535

	Pr(Stock)>0	% FW	Pr(Stock)>0	%FW
% SC Particip.	0.0170*** (0.00326)	0.277*** (0.0977)		
% FC Particip.				
% OC Particip.				
Expec R	0.733** (0.323)	34.49*** (11.53)		
RA	-0.0139** (0.00621)	-0.365* (0.192)		
Controls	Yes	Yes		
Constant	-1.170*** (0.295)	-36.88*** (9.249)		
Log-likelihood	-1206	-3635		
LR $\chi^2$ (p-value)	419.0	373.9		
Pseudo $R^2$	0.166	0.0489		
Observations	2,525	2,294	2,525	2,294

	Pr(Stock)>0	% FW	Pr(Stock)>0	%FW
% SC Particip.	0.0170*** (0.00326)	0.277*** (0.0977)		
% FC Particip.			0.00783*** (0.00195)	0.150** (0.0599)
% OC Particip.			0.00684** (0.00333)	0.147 (0.105)
Expec R	0.733** (0.323)	34.49*** (11.53)	0.678** (0.320)	32.94*** (11.53)
RA	-0.0139** (0.00621)	-0.365* (0.192)	-0.0140** (0.00622)	-0.371* (0.191)
Controls	Yes	Yes	Yes	Yes
Constant	-1.170*** (0.295)	-36.88*** (9.249)	-1.153*** (0.300)	-36.72*** (9.311)
Log-likelihood	-1206	-3635	-1203	-3632
LR $\chi^2$ (p-value)	419.0	373.9	422.7	379.5
Pseudo $R^2$	0.166	0.0489	0.168	0.0497
Observations	2,525	2,294	2,525	2,294

# Findings

- Information effect on stock market through expectations small
- Information effect sizable on decisions (both Tobit and Probit), conditioning on expectations
- E.g. if No. of people from the FC of a **typical investor** that follows the stock market goes up by 1

then this is associated with an increase in the % of financial wealth invested in the stock market of about **5 pp**

(corresponds to about €5K more invested in stocks for the average investor)

- Imitation effect absent...
- Although there are smaller albeit significant effects of share of **outer circle** participating on both expectations and stockholdings, also respondents' information is more in line with publicly available data  $\implies$  no evidence of mindless imitation (more below)
- Robust evidence supporting a positive effect of **informative social interactions**



## Additional support for information channel

- 1 Effects by *direction of information flow* balance: those who both give and receive advice/information (to and from their FC) invest more in the stock market;
- 2 Perceptions of returns (proxy for how informed respondents are) are more in line with available data the more/better 'connected' individuals are: higher number of informed peers in FC associated with perceived return closer to the true return (i.e. better informed individual);

## Pr(Holding stocks dir. or indir. &gt; 0)

% FC Inform.	0.00844*** (0.00177)	
(% FC Inform.)*(Inform to = Informed from)		0.00941*** (0.00245)
(% FC Inform.)*(Inform to > Informed from)		0.00682*** (0.00240)
(% FC Inform.)*(Inform to < Informed from)		0.00808** (0.00332)
% OC Inform.	0.00126 (0.00317)	0.00228 (0.00312)
No FC		-0.0252 (0.0844)
Controls		Yes
Log-likelihood	-1203	-1200
LR $\chi^2$ (p-value)	422.7	448.3
Pseudo $R^2$	0.168	0.170
Observations	2,525	2,525

## Pr(Holding stocks dir. or indir. &gt; 0)

% FC Particip.	0.00783*** (0.00195)	
(% FC Particip.)*(Inform to = Informed from)		0.0113*** (0.00276)
(% FC Particip.)*(Inform to > Informed from)		0.00542** (0.00253)
(% FC Particip.)*(Inform to < Informed from)		0.00770** (0.00355)
% OC Particip.	0.00684** (0.00333)	0.00780** (0.00340)
No FC		-0.0534 (0.0835)
Controls		
Log-likelihood	-1202	-1201
LR $\chi^2$ (p-value)	435.4	441.9
Pseudo $R^2$	0.168	0.169
Observations	2,525	2,525

E(% Fin.Wealth in Stocks|Hold. Stocks > 0)

% FC Particip.	0.150** (0.0599)	
(% FC Particip.)*(Inform to = Informed from)		0.139* (0.0811)
(% FC Particip.)*(Inform to > Informed from)		0.109 (0.0804)
(% FC Particip.)*(Inform to < Informed from)		0.0739 (0.107)
% OC Particip.	0.147 (0.105)	0.171 (0.106)
No FC		0.249 (2.697)
Controls		Yes
Log-likelihood	-3634	-3634
LR $\chi^2$ (p-value)	376.3	375.7
Pseudo $R^2$	0.0492	0.0491
Observations	2,294	2,294

E(% Fin.Wealth in Stocks|Hold. Stocks > 0)

% FC Inform.	0.142** (0.0575)	
(% FC Inform.)*(Inform to = Informed from)		0.115 (0.0750)
(% FC Inform.)*(Inform to > Informed from)		0.134* (0.0785)
(% FC Inform.)*(Inform to < Informed from)		0.124 (0.105)
% OC Inform.	0.00784 (0.100)	0.0214 (0.0999)
No FC		0.659 (2.732)
Controls		Yes
Log-likelihood	-3632	-3633
LR $\chi^2$ (p-value)	379.5	378.0
Pseudo $R^2$	0.0497	0.0495
Observations	2,294	2,294

### Subjective Perceptions of Returns (Perc. R.)

% SC Inform.	0.000849*** (0.000294)				
% FC Inform.			0.000353* (0.000191)		
% OC Inform.			0.000476 (0.000295)		
% SC Particip.			0.00122*** (0.000336)		
% FC Particip.					0.000323* (0.000193)
% OC Particip.					0.000853*** (0.000310)
Controls			Yes		
Constant	0.0741*** (0.0253)	0.0613** (0.0257)	0.0614** (0.0259)	0.0598** (0.0256)	0.0620** (0.0256)
<i>F</i> ( <i>p</i> – value)	5.430 (0)	5.229 (0)	5.100 (0)	5.397 (0)	5.263 (0)
<i>R</i> <sup>2</sup>	0.0799	0.0841	0.0858	0.0876	0.0885
Observations	2255	2255	2255	2255	2255

# Unobserved heterogeneity

- 1 We split individual social circles into financial and outer: we find no statistical evidence in support of outer circle effects, which also control for unobserved group heterogeneity;
- 2 We include very detailed individual covariates, including questions about how do respondents view themselves relative to the members of the social and financial circles (to control for social utility motives);
- 3 We conduct counterfactual placebo tests, by randomizing individual responses to questions on financial circle information: artificial 'in-sample' bins constructed on age, education and region of residence provide no evidence in support of an unobserved group effect;
- 4 Results robust to selection of peers/acquaintances with whom to interact on respondents' financial matters (IVs 'unwise' and Heckman two-step 'unfeasible'), which supports the identification of an information endogenous peer effect (Blume et al. 2011, 2015).

## Pr(Holding stocks dir. or indir. &gt; 0)

% FC Inform.	0.00226*** (0.000469)		-0.000459 (0.000626)	
% OC Inform.	0.000337 (0.000848)		2.84e-05 (0.00105)	
% FC Particip.		0.00209*** (0.000518)		-0.000543 (0.000646)
% OC Particip.		0.00183** (0.000890)		0.000799 (0.00115)
Expec. R.	0.182** (0.0855)	0.181** (0.0856)	0.213** (0.0951)	0.214** (0.0950)
Controls			Yes	
Log-likelihood	-1202	-1203	-1167	-1126
LR $\chi^2$ (p-value)	435.4 (0)	422.7 (0)	448.7 (0)	444.3 (0)
Pseudo $R^2$	0.168	0.168	0.161	0.165
Observations	2,525	2,525	2,422	2,342



E(% Fin.Wealth in Stocks|Hold. Stocks > 0)

% FC Inform.	0.0359** (0.0145)		0.0109 (0.0185)	
% OC Inform.	0.00198 (0.0253)		0.0252 (0.0309)	
% FC Particip.		0.0378** (0.0151)		0.0110 (0.0194)
% OC Particip.		0.0371 (0.0265)		0.0300 (0.0346)
Expec. R.	8.423*** (2.914)	8.298*** (2.912)	9.395*** (2.974)	9.409*** (2.975)
RA	-0.0958** (0.0483)	-0.0935* (0.0482)	-0.0997** (0.0497)	-0.103** (0.0496)
Controls		Yes		
Log-likelihood	-3634	-3632	-3492	-3381
LR $\chi^2$ (p-value)	376.3 (0)	379.5 (0)	361.5 (0)	353.3 (0)
Pseudo $R^2$	0.0492	0.0497	0.0492	0.0496
Observations	2,294	2,294	2,197	2,124

# Unobserved Heterogeneity: Selection of FC

We treat group choice and behaviour within a group as a set of joint outcomes (Blume et al., 2011, 2015):

$$\begin{cases} \Pr(\text{Stocks}_i > 0) = \Phi(\lambda_0 + \lambda_1 k_i^* + \lambda_2 \text{Expec } R_i + \lambda_3 \rho_i + \tau_i \lambda) \\ \Pr(\text{FC}_i > 0) = \Phi(v_1 [k_{iFC}^* - k_{iOC}^*] + v_2' \text{Expec } R_i + v_3' \rho_i + \tau_i v') \end{cases}$$

where  $k_i^*$  is agent  $i$ 's expectation/perception of the share of peers in his FC informed about the stockmarket, %FC Informed.

We model the choice of a financial circle,  $g = FC$ , based on an overall respondent specific quality measure for each group, i.e.

$Q_{ig} = v_1 k_{ig}^* + v_2 \text{Expec } R_i + v_3 \rho_i + \tau_i v + v_{ig}$ . If  $g = \{FC, OC\}$ ,  $i$  chooses  $\max_g Q_{ig}$  on the basis of only the expected average peer information (or behaviour)

that may occur,  $k_{ig}^* = \{\% g \text{ Informed}, (\% g \text{ Participating})\}$ , then

$$\Pr(\text{FC}_i > 0) = \Pr(Q_{iFC} - Q_{iOC} \geq 0).$$

Main concern: respondents who intend to invest in the stock market, choose within their social circles the peers with whom to discuss their own financial matters. Then  $u_i$  and  $v_{iFC} - v_{iOC}$  correlated,  $u_i = \rho(v_{iFC} - v_{iOC}) + v_i$ , i.e. we should reject the  $H_0: \rho=0$ .

	Pr(Stocks <sub>i</sub> >0)	Pr(FC <sub>i</sub> >0)	Pr(Stocks <sub>i</sub> >0)	Pr(FC <sub>i</sub> >0)
% FC Inform.	0.00814*** (0.00179)	0.0153*** (0.00243)	0.00814*** (0.00179)	0.0101*** (0.00370)
% OC Inform.	0.00147 (0.00316)	-0.00397 (0.00359)	0.00147 (0.00316)	-0.00179 (0.00482)
% FC Partic.				0.00940** (0.00423)
% OC Partic.				-0.00642 (0.00550)
Expec. R.	0.770* (0.399)	0.0748 (0.391)	0.770* (0.399)	0.0549 (0.393)
Controls			Yes	
Log-likelihood	-1709	-1709	-1702	-1702
LR $\chi^2$ (p-value)	723.9 (0)	723.9 (0)	714.0 (0)	714.0 (0)
rho	0.0159	0.0159	0.0154	0.0154
Wald $\chi^2(1)$ H <sub>0</sub> :rho=0	0.105	0.105	0.0971	0.0971
p-value $\chi^2(1)$	0.746	0.746	0.755	0.755
Observations	1684	1684	1684	1684

# Summary and going forward

- Theory suggests that the social interactions should improve investors information about the stock market
- i.e. investors are more likely to trade and trade more the higher the number/quality of 'informed connections'
- We find evidence in favour of this, and delink informative and uninformative social interactions
- The ones that matter for stock market decisions are informative social interactions
- Main result: strong evidence of a **pure information channel**
- No (strong) evidence of mindless imitation in stock market decisions

## Appendix: Separating social from financial circle

Variable	Mean all	Mean inv	Questions
SC	53	53.6	C1
FC	3	3	D1
OC	–	–	C1-D1
%SC Inform.	12.5%	15.8%	C7ii
%SC Particip.	10.6%	15.3%	C7i
%FC Inform.	20.1%	28.2%	D16ii
%FC Particip.	22%	27.7%	D16i
%OC Inform.	–	–	$\frac{C1 \times C7ii - D1 \times D16ii}{C1 - D1}$
%OC Particip.	–	–	$\frac{C1 \times C7i - D1 \times D16i}{C1 - D1}$
%FW	5.32%	21.4%	C19
Pr(Stock>0)	–	–	C19
Perc. R	3.6%	5.1%	C42
Exec. R	1.6%	2.3%	C39
Actual R	> 30%	–	<i>Yahoo Finance</i>

## Appendix: Mean/Median Responses to Expec.R. and Perc.R. Questions

VARIABLES	# obs.	Mean	Median	St. D.	Min	Max
Expec. R	2535	0.0162	0.0000	0.0894	-0.6250	0.625
SD Expec. R	2535	0.0669	0.0500	0.0708	0	0.3875
Perc. R	2328	0.0360	0.0050	0.1204	-0.3750	0.3750
SD Perc. R	2328	0.0664	0.0433	0.0717	0	0.3114

Table: Questions C39 and C42, TNS 2014. Summary Statistics.

# Appendix: Histograms of Mean and St.Dev. of Expec.R.

Histograms of Mean and St.Dev. of Subjective Expectations of Returns; question C39 TNS2014

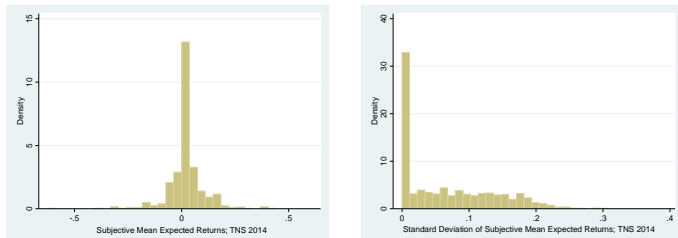


Figure 1a: Histograms of the subjective mean (left panel) expected five-year ahead cumulative return, and its standard deviation (right panel); TNS2014.

# Appendix: Histograms of Mean and St.Dev. of Perc.R.

Histograms of Mean and St.Dev. of Subjective Perceptions of Returns; question C42 TNS2014

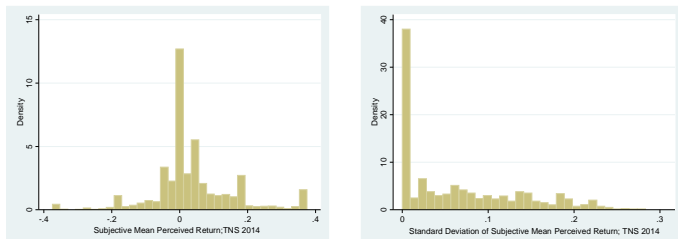


Figure 1b: Histograms of the subjective mean (left panel) perceived three-year cumulative realized return, and its standard deviation (right panel); TNS2014.



VARIABLES	(1) Pr(%FW>0)	(2) Pr(%FW>0)	(3) Pr(%FW>0)
% FC Particip.	0.00646*** (0.00194)		0.00573* (0.00316)
% FC Inform.		0.00535*** (0.00179)	0.000810 (0.00298)
% OC Particip.	0.00298 (0.00327)		0.00276 (0.00441)
% OC Inform.		0.00225 (0.00317)	0.000239 (0.00442)
Perc. R	0.851*** (0.251)	0.863*** (0.250)	0.847*** (0.250)
Controls	Yes	Yes	Yes
LR $\chi^2$ (p-value)	428.03(0)	432.81(0)	434.45(0)
Pseudo $R^2$	0.1516	0.1513	0.1528
Observations	3,670	3,670	3,670

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- *Note: no need to know the exact network structure, only individual connectedness*