INFORMATIVE SOCIAL INTERACTIONS*

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Abstract. We design, field and exploit novel survey data, from a representative sample of the French population in December 2014 and May 2015 to provide insights regarding social interactions and whether they are informative for financial decisions, or they encourage imitation, mindful or mindless. We provide a model where purely informative social interactions influence subjective expectations of future stock market returns and demand for investing in stocks, and find strong support for the presence of informative social interactions. The extent to which the respondent's financial circle is informed about or participates in stockholding appears to influence perceptions of recent stock returns and, only through them, expectations of future returns. Controlling for subjective expectations, stock market participation and the conditional portfolio share are positively influenced by the extent to which the financial circle is informed about or participating in the stock market. Alongside informative social interactions with the respondent's financial circle, we also find some evidence of mindless imitation of stock market participation observed in the outer social circle. These findings suggest that informative social interactions are significant and create a social multiplier for financial education and information, even though the potential for mindless imitation is also present.

Keywords: Information networks; Social interactions; Subjective expectations; Peer effects; Portfolio choice.

JEL Codes: D12, D83, D84, G11, C42.

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1. Introduction

In recent times, financially developed economies experienced dramatic events such as the fast spread of stock market participation in the 1990s leading up to the burst of the dot-com bubble, and the spread of excessive borrowing against home equity leading to the recent global financial crisis. In the face of such large scale and systemically important events, it is natural to ask, what is the role of social interactions and peer effects for the spread of financial behavior in the general population? In this paper, we focus on how social interactions and peer effects affect individuals' decisions to rationally invest in the stock market.[1]

Recent literature broadly identifies two channels via which social interactions may generally affect financial decisions such as investing in the stock market: (i) *information peer effects,* which arise solely from directly communicating and disseminating information to and from friends and acquaintances and (ii) *imitation or endorsement peer effects*, also referred to as those driven by *social utility motives*, broadly understood as comprising of social norm effects in preferences (conformity) or complementarities in production. Information peer effects obtain from agents learning socially, but are distinct from observational learning. Observational learning happens when agents infer the information of their peers only from observing peers' decisions.[2] Both peers' decisions and peers' information should augment individual information sets. Imitation peer effects obtain instead when peers' decisions are adopted without augmenting individual information sets.

Although a rigorous derivation of the equilibrium underpinnings of endorsement effects has recently been advanced for the linear-in-means workhorse econometric specification of social interactions models (Blume, Brock, Durlauf and Jayaraman, 2015), no such a microfoundation exists for information effects. The starting point of our analysis is therefore to model direct communication social learning within a competitive financial market. Agents are privately informed and have access to a large information network, gathering private information from peers, friends and acquaintances (information network) as well as publicly, from equilibrium asset prices. The model extends Ozsoylev and Walden (2011) to heterogeneity in risk preferences and to more general information network structures. A key prediction of the model is that individuals with higher 'connectedness', i.e. with more and/or more informative social interactions, invest in risky assets more aggressively. This is because well-connected individuals pool more and/or more precise privately received signals by individuals they are acquainted with, increasing the precision of their conditional stock market return expectations and thereby, the share of their wealth invested in risky assets.

With this prediction in mind, we design, field and exploit novel survey data that provide measures of stock market participation (relative to individuals' financial wealth), connectedness, but also of subjective expectations and perceptions of stock market returns via probabilistic elicitation techniques. Our empirical analysis exploits cross-sectional variation for a representative sample by age, asset classes and wealth of the population of France, collected in two stages,

[1] See for example Campbell (2016), for a normative motivation in understanding the rationality behind household financial choices.

[2] See Cai, Chen and Fang (2009) for field experimental evidence on the prevalence of observational learning.

in December 2014 and May 2015. In addition to the aforementioned variables, the questionnaire contains a rich set of covariates for socioeconomic and demographic controls, preferences, constraints and access and frequency of consultation of information sources, typically absent from social network empirical studies. Crucially, it also contains specific questions designed to obtain quantitative measures of relevant network characteristics that enable identification of information network effects on financial decisions from individual answers, in the spirit of the classic work by Katz and Lazarsfeld (1955).

There are four key advantages of using our survey data: (i) the actual mechanism whereby social interactions matter for financial decisions can be empirically identified from respondents' answers to questions on beliefs and perceptions of stock market returns, when combined with data on measures of access and frequency of consultation of both publicly and privately available information sources (see Blume et al. 2015); (ii) we can sidestep the 'reflection problem' that arises when social interactions are identified empirically from linear-in-means econometric specifications (see Blume, Brock, Durlauf and Ioannides, 2011), because we exploit variation in respondents' perceptions about peers' behavior (and characteristics) instead of the actual behavior of their peers; (iii) our main identification strategy for disentangling 'informed holdings' from 'uninformed holdings' of risky assets is to separately ask respondents' perceptions about peers' holdings and peers' information, and (iv) the survey is done over a representative sample of a population of a financially developed country (France), with a mature stock market and abundantly publicly available information. Although we cannot trace the actual network structure, neither at the individual level, nor for the whole stock market (DePaula, 2016), this is an inherent feature of the stock market rather than a limitation of our empirical approach. We are able to focus on perceptions that respondents have and on the basis of which they make stockholding choices, even though we cannot validate the extent to which individual perceptions about peer information or behavior correspond to their objective counterparts.

Our empirical analysis suggests that an information effect indeed obtains from social interactions, first on perceptions of the past and, through them, on expectations of future stock market returns; and second, on whether and how much respondents invest in the stock market, controlling for subjective stock market expectations.

To reinforce our evidence of an information channel and address the possibility that our estimates simply reflect unobserved heterogeneity, we put to use an interesting interpretation of the theoretical model in the design of the survey in the spirit of Grinblatt, Kerlohaju and Ikäheimo (2009). Specifically, our theoretical framework suggests that aside from the usual social circle of friends and acquaintances of an individual, we can also identify a subset of it which we call the *financial circle*, i.e. members of the respondent's social circle with whom the individual specifically interacts on financial matters, e.g. investments. Implicit in this distinction is the fact that members of the financial circle have been specifically selected to discuss financial matters, because they are more knowledgeable and the respondent trusts their views (in the context of the theoretical model, members of the financial circle are considered to have more precise, informative signals). By asking respondents to directly report numbers and information about their financial circle, we can generate variables that correspond to both their financial circle and their *outer circle* (i.e. all those remaining members of respondents' social circles with whom they do not discuss financial matters).

With this novelty in place, we can address three issues in one go. First, we can reinforce our main conclusion that there is a strong and significant information effect present: we find that when we regress expectations, perceptions or the share of financial wealth invested in the stock market on the proportions of one's financial and outer circles that are perceived to follow the stock market controlling for household characteristics, the effect of the former is sizeable and significant, while the effect from the latter is statistically insignificant. The interpretation of this is that information about the stock market simply does not pass from the outer circle to the respondents, because respondents do not discuss financial matters with them.

Second, it allows us to separately identify observational learning from mindless imitation in financial decisions. By mindless imitation we mean that respondents follow the financial behavior of others in their circle, due to e.g. peer pressure, conformity or a fad effect. Observational learning instead obtains when the respondent emulates the behavior of those in one's circle that are considered knowledgeable and trustworthy about financial matters. If observational learning is present, we consider social interactions as being *indirectly* informative as opposed to observing peers' signals, which are *directly* informative. We find no evidence in support of mindless imitation with respect to expectations, perceptions or conditional portfolio shares. We do find some evidence of mindless imitation, though, when it comes to the decision to participate in the stock market. With the advent of modern technology, the spread of social media, and the establishment of online investment and lending platforms, one can expect informative social interactions, but also the potential for mindless imitation to grow in importance.

Third, our approach of splitting the social circle of respondents into financial and outer circle helps us tackle the issue of unobserved heterogeneity. If indeed respondents and their social circles all follow and/or invest in the stock market (or not) because people tend in general to socialize with those that are similar to them and face common unobserved factors, then we would expect to see positive and significant effects of the knowledge and participation of both the financial and outer circles on the share of financial wealth invested in the stock market by respondents. The fact that the effects from the outer circles are insignificant, except for the stock market participation decision, indicates that it is not the similarities in people's circles that matter for their stock market decisions, but rather their informative social interactions with members of their financial circle. This conclusion is reinforced through placebo tests, where perceptions regarding the financial and outer circles are reshuffled among respondents of the same age, education, and region (department). To overcome the possibility of selection bias, we also allow for respondents to select friends and acquaintances with whom to exchange on their own financial matters jointly with whether to invest in stocks or not, but fail to find any evidence in support of correlated unobserved factors in these two decisions.

Within the financial literacy literature (e.g. Lusardi, et al. 2016; Campbell, 2016), our work is related to a budding literature examining peer effects on asset and debt behavior of households (see Hong, et al., 2004, and Georgarakos, Haliassos and Pasini, 2014 respectively) and a more voluminous one examining the effect of subjective expectations on individual economic and financial behavior (summarized by Hurd, 2009, and more recently, by Greenwood and Schleifer, 2014); but also closely related to the literature on the effects of social imitation and influence on financial behavior in competitive markets within the larger literature on social and information networks (e.g. Jackson, 2008).

Most related to our work is Bursztyn et al. (2014), who conduct a field experiment in collaboration with a Brazilian brokerage firm in order to disentangle endorsement from information peer effects on the willingness to invest in a brand new financial product. For such a product, they conclude that both motives are important in individual financial decision making and that the social learning channel is relatively more important than the social utility channel amongst more sophisticated investors. Also related is the experimental work by Banerjee et al. (2013) who study a newly introduced micro-finance program in rural India and conclude that most of peer effects on the take-up rates of the program are due to an information channel.[3] The main difference with these papers is our focus on a well-known, mature financial product (stocks) in the general population of a financially developed country without restrictions on information flows. The similarities and differences with these papers are further evaluated, in light of our findings, in Section 4.

2. The Model

Ozsoylev and Walden (2011) provide a microfoundation for an information network effect within a rational model of equilibrium asset pricing where prices and private signals about asset returns transmit information. We extend their model to guide our survey design and empirical strategy. In what follows, we present a brief overview of the model, the generalization of their theorem and explain how the derived individual asset demand function will be used as a guide for identifying information peer effects.

There are two assets, one risky (stock) and one risk free (bond). The payoff of the risk free 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. The supply of stocks is random and is given by $Z_n = nZ$, where $Z \sim N(\bar{Z}, \Delta^2)$ and $\bar{Z} > 0$. [4] The final wealth of the agent is

$$\omega_i = \omega_{0i} + D_i \left(X - p\right) \tag{1}$$

where ω_{0i} is the initial wealth of agent i. Agent i chooses D_i units of the risky asset to maximize expected utility from final wealth, conditional on his information set $\mathcal{I}_i$. Assuming CARA preferences

$$u\left(\omega_i\right) = -e^{-\rho_i \omega_i}$$

where ρ_i is the absolute risk aversion of agent i, an agent thus solves the problem

$$\max_{D_i} \mathbb{E}\left[u\left(\omega_i\right) \mid \mathcal{I}_i\right] = \max_{D_i} \mathbb{E}\left\{-\exp\left[-\rho_i\left(\omega_{0i} + D_i\left(X - p\right)\right)\right] \mid \mathcal{I}_i\right\}. \tag{2}$$

[3] Empirical work by Ozsoylev et al. (2014) exploits stock market transactions data to identify an empirical investor network from the time proximity between individual transactions.

[4] See Easley et. al. (2013) for discussion on positive supply of risky assets and liquidity traders.

and thus

$$D_i^* = \frac{\mathbb{E}\left[(X - p)\,|\mathcal{I}_i\right]}{\rho_i Var\left[X|\mathcal{I}_i\right]}. \tag{3}$$

Every agent i receives a primary (agent specific) piece of information in the form of a signal on the risky asset payoff $y_i = X + \epsilon_i$, $\epsilon_i \sim N(0, s_i^2)$. We allow heterogeneity across the variance of the signals of the agents, to reflect the fact that agents may have more or less precise information about the risky asset for exogenous reasons.

Investors may know each other socially and these links are captured by an adjacency matrix A, where the typical element a_{ij} can take value 1 or 0, if agents i and j know each other or not, respectively. We allow for loops, i.e. we let $a_{ii} = 1$, for all agents. Since $a_{ij} = a_{ji}$, the matrix A is symmetric. For an investor i, his social circle is then defined by his network neighborhood, i.e. all investors j, such that $a_{ij} = 1$.

To describe the financial circle of an investor, we define an additional adjacency matrix G which describes the financial network. Investors determine their demand for the risky asset by pooling their own private information about its return, with private signals of investors with whom they interact socially. An investor combines his own signal with those of his neighbors to generate his payoff signal x_i, by averaging the signals of his social circle, *weighted* by their corresponding precisions. In particular, the weight on the signal of investor j used by investor i, is assumed to be the precision of the signal of agent j.[5] From the perspective of agent i, when he pools all the signals from his neighbors, he then puts more weight on agents with precise signals and less weight on those with less precision. The typical element of matrix G is then

$$g_{ij} = \ \{\text{information is passed on from agent } j \text{ to agent } i\} = \frac{a_{ij}}{s_j^2},$$

in other words, $G = A\Sigma^{-1}$, where $\Sigma = diag\left\{s_1^2, ..., s_n^2\right\}$. We note that G represents a weighted and directed network. Let

$$k_i = \sum_{k=1}^{n} \frac{a_{ik}}{s_k^2} \tag{4}$$

be the *connectedness* of investor i.[6] The pooled payoff signal x_i for agent i is:

$$x_i = \frac{\sum_{k \in R_i} y_k}{d_i} \equiv \frac{\sum_{k=1}^n g_{ik} y_k}{\sum_{k=1}^n g_{ik}} = X + \frac{\sum_{k=1}^n g_{ik} \epsilon_k}{\sum_{k=1}^n g_{ik}}. \tag{5}$$

The assumption that the network is weighted by signal precision captures the fact that investors put more importance on good quality information they receive from the social circle.

Next, let $r_{ij} = g_{ij} / \sum_{k=1}^n g_{ik}$ be the intensity of the link between nodes i and j, which defines

[5] We can also assume it to be the *relative* precision of the signal of agent j, i.e. the precision of j's signal over the precision of i's signal. This is a more attractive assumption, but complicates unnecessarily the mathematical expressions of the assumptions needed in deriving the optimal demand function, without affecting the formal expression of our econometric specification.

[6] This is a generalization of the well known concept of degree, or strength, which counts the number of links of a network node.

the intensity matrix $R = [r_{ij}]$. Then, we can define

$$\mathbf{S} \equiv Cov\left(R\boldsymbol{\epsilon}\right) = R\Sigma R^T.$$

Finally, given the information network, investors' information sets are defined by

$$\mathcal{I}_i = \{x_i, p\}, \forall i = 1, ..., n \tag{6}$$

because also asset prices are allowed to transmit information in equilibrium, and investors rationally anticipate it. We note that the random variables X, Z and ϵ_i are all *jointly independent.*

Under a set of assumptions on the asymptotic nature of the network structure as the number of investors n grows, we extend Theorem 1 of Ozsoylev and Walden (2011).[7] Broadly speaking, the assumptions require that the information network is sparse, i.e. that the strength of connections between agents are of the same order as the number of nodes, and that no agent is informationally superior in the large financial market (as $n \to \infty$). The average connectedness β of the large information network is defined via the assumption that

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

which imposes that the average node strength, weighted by risk aversions, is finite. Then, it can be shown that there exists a linear noisy rational expectations equilibrium as $n \to \infty$, such that with probability one the risky asset price converges to

$$p = \pi_0^* + \pi^* \bar{X} - \gamma^* \bar{Z}, \tag{7}$$

where

$$\begin{aligned} \pi_0^* &= \gamma^* \left(\frac{\bar{X}\Delta^2 + \bar{Z}\beta\sigma^2}{\sigma^2\hat{\rho}\Delta^2 + \sigma^2\beta} \right), \\ \gamma^* &= \frac{\sigma^2\hat{\rho}\Delta^2 + \beta\sigma^2}{\beta\sigma^2\hat{\rho}\Delta^2 + \Delta^2 + \beta^2\sigma^2}, \\ \pi^* &= \gamma^*\beta. \end{aligned}$$

and $\hat{\rho}$ denotes the finite harmonic mean of risk aversions of all agents in the population.

In determining the optimal demand for the risky assets, agents form a subjective expectation of the return on the asset, based on the average signal of their social circle. In equilibrium, and as $n \to \infty$, the expected return for an investor i is given by

$$\mathbb{E}\left(X|\mathcal{I}_i\right) = \frac{k_i^*\sigma^2\Delta^2}{k_i^*\sigma^2\Delta^2 + \Delta^2 + \sigma^2\beta^2} x_i + \left(\frac{\sigma^2\beta^2 + \Delta^2}{k_i^*\sigma^2\Delta^2 + \Delta^2 + \sigma^2\beta^2} \right) \bar{X}, \tag{8}$$

where $k_i^* = \lim_{n\to\infty} k_i$. This suggests that larger connectedness k_i^* implies that investors expectations react more strongly to their pooled signal. Moreover, in equilibrium, the asymptotic

[7] The set of assumptions and the precise statement of the Theorem can be found in Appendix A.

demand for the risky asset by an agent i is:

$$D_i^* \equiv D_i^*\left(x_i, p\right) = \frac{\hat{\rho}}{\rho_i}\left(\frac{\bar{X}\Delta^2 + \bar{Z}\beta\sigma^2}{\hat{\rho}\sigma^2\Delta^2 + \sigma^2\beta}\right) - \frac{\hat{\rho}}{\rho_i}\left(\frac{\Delta^2}{\sigma^2\left(\hat{\rho}\Delta^2 + \beta\right)}\right)p + \frac{k_i^*}{\rho_i}\left(x_i - p\right). \tag{9}$$

This expression suggests that for a given average risk-adjusted connectedness β, individual connectedness affects demand via two channels: directly via the elasticity k_i^*/ρ_i with respect to the conditional excess return $(x_i - p)$, and indirectly through its effect on the excess return (i.e. *within* x_i).

The model therefore predicts that higher connectedness makes investors trade more aggressively, conditional on investing in the stock market: higher connectedness implies higher demand for risky assets. In addition, higher k_i^* may be the result of two effects: (i) larger number of acquaintances (i.e. larger number of agents for which of $a_{ij} \neq 0$) and/or (ii) higher signal precision of the signals that individual i pools from her/his social interactions. We are interested in both predictions, but mostly on the second interpretation: that the more informative one's social interactions are (i.e. as the precision of an individual's pooled signals improves), the more his/her demand for the risky asset responds to his/her pooled signals, and thereby, their conditional excess return. This is the *information effect* from informative social interactions that we seek to empirically identify exploiting our survey data.

To guide our empirical strategy, we note that both the expressions for expected returns (8) and equilibrium individual demands (9) require us to only know the average connectedness β and the individual connectedness of investors, k_i^*, and not the exact general structure of the network. Therefore in designing the survey, a representative sample from a large population for which we can identify measures for k_i^* is sufficient to empirically identify an information peer effect.

3. Survey Design

In this section, we provide a brief description of the survey design and the specifically designed questions we exploit. More detailed information about both is provided in Appendix B. The survey is part of an ongoing survey of the French population administered by Taylor-Nelson Sofres (TNS). We design and exploit data from two questionnaires that were fielded in December 2014 and May 2015 respectively. The first questionnaire (2014 wave) contains questions that provide very detailed information on attitudes, preferences, expectations and perceptions of stock market returns, in addition to wealth, income and socioeconomic and demographic characteristics for a representative sample of French households by age, wealth and asset classes. The follow-up questionnaire (2015 wave) contains a variety of questions that specifically aim at gathering information about respondents' social and financial circles, their compositions, as well as at how respondents' financial decisions depend on the decisions and information of their friends and acquaintances.

The 2014 questionnaire was sent to a representative sample of 4,000 individuals, corresponding to an equivalent number of households. Respondents had to fill the questionnaire, and return it by post in exchange for €25 in shopping vouchers (*bons-d'achat*). Of those, 3,670 individuals sent their questionnaires back, representing a 92% response rate. The follow-up questionnaire in May 2015 was sent to the 2014 wave of 3,670 respondents, out of which we recovered a total of 2,587 responses, corresponding to a response rate of 70.5%.

The relevant questions that inform our empirical analysis can be grouped in four sets. First, we have questions that directly ask respondents to state what is their total financial wealth (excluding housing), and of this wealth, what share they invest in the stock market (directly or indirectly). The latter defines variable $\%FW$ which captures the demand for risky assets conditional on participating in the stock market. From the same question, variable $\Pr(Stocks > 0)$ obtains, taking value 1 if respondents have a positive share of their financial wealth invested in the stock market, and zero otherwise.

The second set of questions asks respondents to state their expectations about a public non-manipulable event (e.g. the expected return on a buy-and-hold portfolio that tracks the evolution of the stock market index, CAC-40, over a five-year time window), in order to understand if it determines their current financial behavior.[8] The recent literature on measuring expectations privileges the use of probability questions rather than eliciting point expectations or the traditional qualitative approach of attitudinal research (Manski, 2004). Answers to such questions are then used to understand if expectations and outcomes are related, and to evaluate if individual behavior changes in response to changes in expectations. Crucially, we also include questions that inquire respondents about their perceptions regarding the most recent realization of the same measure (e.g. the most recent realized cumulative return on a buy-and-hold portfolio that tracks the evolution of the stock market index over a three-year horizon). These questions are designed with the following four goals in mind. First, the use of five years as a forecasting horizon helps untie expectational answers from business cycle conditions prevailing at the time of fielding the surveys, to better capture (i) the historic average upward trend of the stock market index, and (ii) inertia in portfolio management (e.g. see Bilias et al., 2010). The latter is important, since it remains an open question with what horizon in mind households invest in the stock market. Second, probability densities are elicited on seven points of the outcome space, instead of just two points of the cumulative distribution functions, to obtain more precise individual estimates of the relevant moments.[9] Third, we exploit data from a representative sample by age, to better account for the hump-shaped age-portfolio profiles at both margins recently identified in the literature (Fagereng, et al., 2016). Fourth, probabilistic elicitation of the most recent cumulative stock market return (over a three-year horizon) provides a quantitative measure of households' degree of awareness regarding their investment opportunity set, to capture differences in information across households as well as the relationship between information and expectations.[10] Without it, households who do not invest because they expect

[8] Dominitz and Manski (2007) elicit probabilistically individuals' expectations of stock market returns inquiring about how 'well' the respondent thinks the economy will do in the year ahead. They exploit data for a representative sample of the elderly from the 2004 wave of the U.S. Health and Retirement Study (HRS).

[9] This follows the methodology of the Survey on Household Income and Wealth (SHIW) conducted by the Bank of Italy (Guiso et al., 1996).

[10] As an example of the former, Armantier et al. (2014) document substantial differences across households regarding the most recent US inflation rate. As an example of the latter, Afruzi, Coibion, Gorodnichenko and Kumar, (2016) examine the relationship between inflation expectations and perceptions of inflation in a sample

the stock market to drop over the given forecasting horizon are indistinguishable from those who do not invest because they are unaware of the investment opportunities available in the stock market. We use responses to questions C39 and C42 (from TNS2014) to generate variables *Expec. R* and *Perc. R* respectively, which in turn are used as proxies for expected conditional returns $\mathbb{E}(X|\mathcal{I}_i)$ and for perceptions of realized returns (based on signals) x_i.

Third, the questionnaire contains a set of questions that are designed to identify the social circle of respondents and will be used for the empirical analysis. The aim is generate meaningful proxies for the individual connectedness k_i^* of each respondent. A main novelty of the survey is to distinguish between a broad circle of social acquaintances of respondents (*social circle*) and a smaller circle within it, defined as the respondents' acquaintances with whom the respondents convene about financial matters (*financial circle*). We separately identify both from responses to the following survey questions respectively (translated wording):

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 own financial/investment matters?*

Of the 2,587 respondents that returned the TNS2015 questionnaires, about 90% and 87% answered questions C1 and D1 respectively. The average number of people in the respondents social circles and financial circles is 52.5 and 3.1 people respectively. About half of the valid responses for question D1 were zero, so we therefore also report that the average of the remaining half (i.e. not taking into account the zeros) is approximately 5 people. Question C1 is formulated with the network of social acquaintances in mind, as described by adjacency matrix A in Section 2. For respondent i, the answer to C1 provides an approximation of the respondent's degree, defined by $\sum_{j=1}^{n} a_{ij}$. Question D1 defines a subset of the people from the respondent's social circle, and is formulated in order to generate broadly a proxy for the elements of matrix G, i.e. a statistic of whether information about the stock market is passed on from acquaintance j to respondent i. It is implicit in the formulation of D1 that respondents discuss financial matters with members of this inner circle, but do not do so with the remaining members of the social circle. In other words, we work with the presumption that respondents may be able to extract information (signals) about the stock market from the members of the financial circle, i.e. that (with normalized precision) if an acquaintance belongs in the respondent's financial circle, then $g_{ij} = a_{ij}$. On the other hand, other acquaintances are excluded from the financial circle, if their signal precision is 0 (i.e. when respondents state that they do not interact with them regarding financial matters), and in that case $g_{ij} = 0$. This allows us to naturally define a third circle for each respondent, which is the social circle excluding the financial circle, namely the *outer circle*. Responses regarding the outer circle of respondents are used for reinforcing the argument in favor of an information channel in making financial decisions that comes from informative social interactions.

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of CE/FOs of New Zealand firms.

Last, we elicit respondents' point perceptions about how many of their friends and acquaintances are interested in and informed about the evolution of the stock market. A similar question format has been successfully exploited by researchers at the Dutch National Bank and at the University of Tilburg (CentER Panel) when identifying social interactions on individual outcomes, since it helps in overcoming the reflection problem identified by Manski (1993).[11] When combined with respondents' point perceptions about the proportion of their friends and acquaintances that invest in the stock market, we hope to disentangle endorsement and information effects from social interactions. There are two sets of questions in this group. The first asks respondents to report what share of their social circle (i) invests and (ii) is informed about the stock market while the second asks the same, but for the financial circle. The exact wording of the questions are:

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 follows the stock market? (as a %)*

Of the 2,587 respondents that send back the TNS2015 questionnaires, about 96% and 88% of respondents provided valid answers for questions C7 and D16 respectively.[12] The cross-sectional average point estimates for the perceived percentage of the social and financial circle that invests in the stock market is 10.6% and 20.1% respectively. Also, the cross-sectional average point estimates for the perceived percentages of the social and the financial circles that follows the stock market are 12.4% and 21.9% respectively. These questions define directly variables $\%SC\ Particip.$, $\%FC\ Particip$, $\%SC\ Inform.$ and $\%FC\ Inform.$ The perceived percentage of the outer circle of a respondent that invests in or is informed about the stock market is obtained from

$$\%OC\ Particip. \equiv \frac{C1 \times C7i - D1 \times D16i}{C1 - D1}, \tag{10}$$

$$\%OC\ Inform. \equiv \frac{C1 \times C7ii - D1 \times D16ii}{C1 - D1}. \tag{11}$$

For notational convenience we use the abbreviations *SC*, *FC*, *OC* for the social circle (defined by C1), financial circle (defined by D1) and outer circle (defined as answer to C1 - answer to

[11] The reflection problem refers to the impossibility of separately identifying the effect of peers' *choices* (endogenous or peer effects) from the effect of peers' characteristics (contextual effects) on individual outcomes, when individual and peers' choices are made simultaneously and as a function of common contextual factors. Here, instead of considering peers' actual choices, we exploit the variation in individual perceptions about peers' choices (e.g. stockholding status), which when combined with individual perceptions about peers' characteristics (e.g. peers' information), enables identification. Li and Lee (2009) actually find that subjective perceptions about peers' behavior in a social interactions model of voting, predicts better individual outcomes than a model where instead (rational expectations) equilibrium beliefs are assumed. See Blume et al. (2011, 2015) for additional details.

[12] In answering each of the questions, the respondent was also given the option to tick the box '*I do not know*'. About 64% and 61% chose this option for questions C7i and D16i respectively. About 61% and 58% reported this option for questions C7ii and D16ii, respectively.

D1) respectively. We also use various other abbreviations for presentation purposes that are all summarized in Table 1. Definitions, exact question statements and detailed explanations on the variables and the survey questions can be found later in the paper and in Appendix B. Table 5 provides summary statistics for the variables we use in the analysis.

4. Empirical analysis

Consistent with our theoretical analysis, in which equilibrium depends on the connectedness, k_i^*, rather than on the precise identity of interacting agents, we employ measures of such connectedness in our empirical analysis. Specifically, we focus on whether and how expectations, perceptions, and behavior are influenced by the share of the relevant peer circle that the respondent considers informed about or participating in the stock market.

4.1. Putting the social and financial circles into context. Our assumption in the theoretical model is that respondents meet their peers and weigh the information they obtain from them according to how reliable they perceive their peers to be. In real life, it is natural to think of respondents as forming a financial circle, in the sense of a subset of their overall social circle with whom they feel confident to discuss financial matters. Respondents are indeed asked whether they have such a financial circle, as well as their perceptions regarding attributes of their social circle and their financial circle, and they report their perceptions as to the shares of both circles that are (i) informed about the stock market and (ii) participating in the stock market. It is important to stress that our data do not record actual shares of informed or participating peers, which may or may not be known to respondents, but shares as they are *perceived* by respondents who form expectations and decide on own stock market participation and exposure.

For respondents who declare having formed a financial circle, we use expressions (10) and (11) to compute their implied perceptions regarding members of their social circle with whom they do not discuss finances. The distinction between a financial and an outer circle is very useful for checking whether our results might be caused by unobserved heterogeneity rather than peer influences; and in distinguishing between exchange of information and mindless imitation of stockholding behavior. Specifically, it is possible that there are unobserved factors influencing the respondent's stock market expectations, perceptions or behavior, as well as whether their peers are informed about, or participating in the stock market. These unobserved factors might induce a correlation between responses and peer attributes without implying any effect from peers on respondents. If respondent stock market expectations, perceptions or behavior reflect simply unobserved dimensions along which respondents are similar to their peers, we would expect correlations to be present whether we consider the financial circle or the outer social circle not privy to financial matters. If, however, only the financial circle but not the outer circle matters for subjective expectations, perceptions, or behavior related to stockholding, then this is evidence against unobserved heterogeneity creating the empirically observed relationship.

The split between a financial and an outer circle can also shed some light on whether social interactions take the form of mindless imitation or exchange of information and possibly mindful imitation of peers perceived as knowledgeable about the stock market. As an example, we would not expect the behavior of the outer circle, with whom respondents do not discuss financial matters, to influence respondents' stockholding behavior directly unless there is pure imitation without the exchange of information. On the other hand, interactions with the financial circle can be informative and contribute to a revision of perceptions about the past performance of the stock market, expectations about the future, or choices regarding stockholding.

We also note here that the survey questions elicit the shares of informed and participating peers in the financial and overall social circles only. We use these two responses to construct the corresponding share of peers in the outer circle, i.e., the complement of the financial circle to the overall social circle. As our approach is indirect, it can sometimes lead to outer-circle shares that fall below zero or exceed 100%. When this happens, we adopt a conservative approach to potential inconsistency: we set both the direct response on the financial circle and the implied for the outer circle to 'missing observation', and we introduce an inconsistency dummy variable (IC) to flag such observations. All reported estimates on the two circles explicitly control for observed inconsistencies in responses.

4.2. Expectations and perceptions. Existing empirical studies of peer effects on financial behavior focus on outcomes, such as stockholding, retirement saving, or debt outstanding. We begin our analysis by investigating the role of social interactions for the formation of subjective return expectations about the future, as well as of perceptions regarding past stock market performance. As expectations are an important determinant of the demand for risky assets, this analysis is interesting both in its own right and as a component of the link to stockholding behavior.[13]

To investigate the empirical relevance of perceptions regarding interacting peers for subjective expectations of stock market returns over the next five-year period, we linearize expression (8). This suggests two empirical specifications:

$$Expec.\ R_i = \kappa_0 + \kappa_1 k_i^* + \boldsymbol{\tau}_i \boldsymbol{\kappa} + e_i \tag{12}$$

and

$$Expec.\ R_i = \kappa_0 + \kappa_2 D_i^e + \boldsymbol{\tau}_i \boldsymbol{\kappa} + e_i, \tag{13}$$

where k_i^* is an indicator of connectedness to the peer circle, D_i^e is an indicator of peer behavior (participation in the stock market), $\boldsymbol{\tau}_i$ is a vector of individual characteristics, e_i is an individual zero-mean error term distributed normally conditional on covariates, and the same coefficient symbols are used for notational economy but not to imply equality of coefficients.

Implementing either specification might raise concerns regarding the role of unobserved

[13] Standard models of financial choice under uncertainty predict that decisions should be based on expectations of future aggregate market outcomes, and not on publicly available information about recent market outcomes, since the latter should be incorporated into respondents' expectations upon conditioning (Brandt, 2010). Indeed, a recent strand of empirical literature finds that subjective expectations are significantly related to financial decisions (e.g. Dominitz and Manski, 2007; Kezdi and Willis, 2009; Hurd et al., 2011).

heterogeneity. Unobserved factors affecting all peers, including the respondent, could be creating a tendency for peers to be perceived as informed about the stock market (participating in the stock market) and simultaneously for the respondent to be having higher or lower expectations about future stock market returns. This could induce a relationship between the percent of the social circle being informed and the reported subjective expectation without any causal implication running from perceived peer information (participation) to respondent expectations.

As a first approach to handling this problem, we distinguish perceptions regarding two peer circles: the inner (financial) circle with whom respondents report that they discuss financial matters; and the rest of their social circle, with whom they report that they do not discuss such matters. We investigate whether either share is significantly related to the respondent's subjective expectation about future stock market returns after controlling for a range of observable respondent characteristics. By splitting the social circle into a financial circle and an outer circle, we are able to apply a "double ring" methodology to identification. If unobserved heterogeneity is an important problem, then it should affect both the financial circle and the outer social circle. Thus, finding a different result for the inner circle than for the outer suggests that the difference is not due to unobserved heterogeneity, since such heterogeneity would necessarily affect both circles.

The empirically implemented specifications are:

$$Expec.\ R_i = \kappa_0 + \kappa_{1,FC} k^*_{i,FC} + \kappa_{2,OC} k^*_{i,OC} + \boldsymbol{\tau}_i \boldsymbol{\kappa} + e_i$$

and

$$Expec.\ R_i = \kappa_0 + \kappa_{1,FC} D^e_{i,FC} + \kappa_{2,OC} D^e_{i,OC} + \boldsymbol{\tau}_i \boldsymbol{\kappa} + e_i.$$

We are able to control for a wide range of characteristics and attitudes of the household head. These include demographic characteristics (age, gender, marital status, number of children), elicited risk preferences (coefficient of absolute risk aversion), a proxy for individual information (self-reported individual perception of the most recent realized stock market cumulative return), proxies for resources and constraints (educational attainment, employment status, assets, income, perceived borrowing constraints, and achieved liquid saving over the past year), and region of residence.[14] In all specifications, we also include dummies for item non-response and inconsistent responses, especially to the expectations and perceptions questions about peer behaviour.[15]

Despite the fact that all respondents were asked about the same stock market, there is considerable variability in responses, both with regard to perceptions regarding its evolution prior to the data collection and with regard to subjective expectations regarding future stock returns. Figure 1 shows historical monthly data of the French stock market index CAC-40, from March 1990 to June 2016. The index dropped by nearly 25% at the time of the sovereign-debt

[14] Detailed variable definitions are to be found in Appendix B.

[15] Controlling for item non response to those questions hardly affects the sign, size, and significance of the main coefficients of interest, namely on perceptions regarding peers. A similar robustness exercise in the presence of missing data can be found in Dimmock, et. al. (2016).

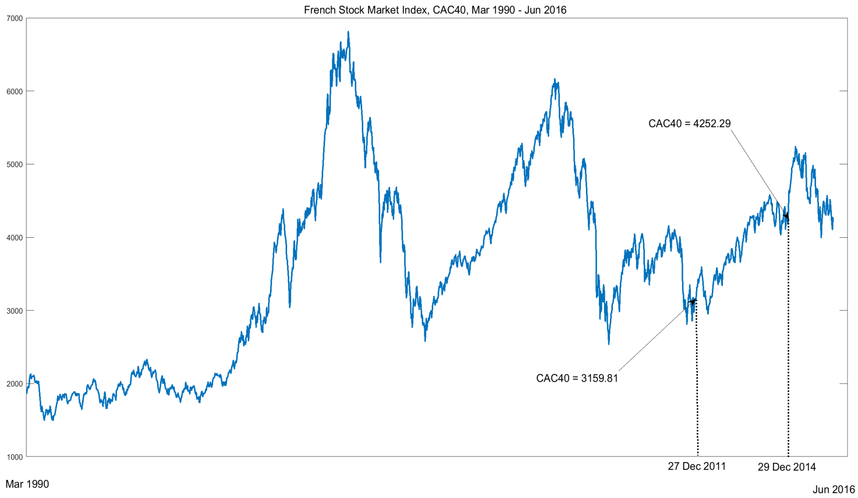

Figure 1: French stock market index, CAC 40, weekly data, 3 March 1990 - 27 June 2016. Source: Yahoo Finance.

crisis during the second half of 2011. After that and as we get closer to the time that the survey and its follow-up questionnaire were fielded, the stock market index has been steadily recovering. Both in late December 2014 and May 2015, the index was still below its dot-com and Lehman brothers peaks, but had already recovered relative to the sovereign-debt crisis. Given the substantial turmoil experienced by the stock market index over the period prior to data collection, respondents are likely to have been exposed to considerable news coverage of the stock market evolution, and this makes the observed variation in perceptions and expectations all the more striking.

Specifically, the actual stock market return over the three-year period in question (Dec 2011 - Dec 2014) was actually +34.57%, but the cross-sectional average perception of respondents regarding returns over the same period is equal to +3.6%. The average cross-sectional subjective expectation of respondents regarding future returns is equal to +1.6%. Positive deviations of perceptions from the low cross-sectional mean and greater optimism than the average observed among respondents of given characteristics in the sample seem consistent with the respondent having more informed perceptions and expectations.

Table 2 reports estimates from these two specifications for subjective expected returns. The regression specification in column (1) includes, in addition to the usual household controls, respondent perceptions regarding how informed members of the two peer circles are. It can be seen that the share of the financial circle that the respondent regards as informed about the stock market is positively and significantly related to the respondent's subjective expectation of future return. By contrast, the corresponding share of the outer circle is found to be statistically insignificant. This difference in results suggests that the observed significant correlation is not simply due to unobserved heterogeneity and creates a presumption in favor of a causal effect from the financial circle that we will subject to further scrutiny below. The specification in column (2) focuses on the shares of the financial and of the outer circle that the respondent perceives as participating in the stock market. Again, we find that the share of stockholders in the financial circle has a (positive) and statistically significant relationship to subjective expected stock market returns, while the corresponding share in the outer circle does not.

Beyond their econometric motivation, the different findings for the two circles also have implications for the likely role of information, rather than mindless imitation, in the interactions among peers. First, and in both specifications, it is perceptions about the financial and not the outer circle that are related to subjective expectations. This is the circle with which respondents discuss financial matters and with which information exchange rather than mere observation of behavior is most likely to occur. Second, both perceived attributes of the financial circle that were found to be significant are likely to generate information for the respondent: the share of the financial circle being informed and the share holding stocks and thus knowledgeable about them. The information and participation patterns of the outer social circle, not deemed reliable for discussion of financial matters, are not related to stock market expectations of respondents.

Columns (3) to (5) of Table 2 introduce subjective perceptions of recent stock price growth (over the past three years) in the regression of subjective expectations about the future of the stock market.[16] Answers to question C42 in our survey enable probabilistic elicitation of respondents' perceptions about the most recent realized cumulative stock market return over a three-year period.[17] We focus on the mean of each respondent's subjective probability distribution over the size of the realized three-year stock market return. For brevity, we will be referring to this as the respondent's perceived return, with the previously introduced notation $Perc.R$.

We see that perceived returns are strongly statistically significant in the subjective expectations regressions, controlling for respondent characteristics, regardless of whether peer variables are included in the regression or not. Strikingly, neither the share of informed peers nor the share of stockholders in the peer circle retain their statistical significance in the presence of subjective perceptions regarding the recent past return. This finding suggests that respondent perceptions regarding how informed their financial circle is or how extensively its members participate in the stock market influence subjective expectations of future returns only to the extent that they influence perceptions of recent past returns.

Next, we examine empirically how perceived returns R_t^i are associated with perceptions about peer information, k_i^*, or group stockholding behavior, D_i^e, as follows:[18]

$$R_t^i = Perc.\ R = \eta_0 + \eta_{1,FC} k_{i,FC}^* + \eta_{1,OC} k_{i,OC}^* + \mathbf{v}_i \boldsymbol{\eta} + \varrho_i, \tag{14}$$

or

$$R_t^i = Perc.\ R = \eta_0 + \eta_{2,FC} D_{i,FC}^e + \eta_{2,OC} D_{i,OC}^e + \mathbf{v}_i \boldsymbol{\eta} + \varrho_i, \tag{15}$$

[16] Measuring individual information sets is difficult even in experimental settings, but some progress has been made by extending Manski's (2004) probabilistic elicitation techniques to facts (as opposed to events), as in Arrondel et al. (2014) or Afrouzi et al. (2016).

[17] The exact wording of the question, details about the construction of the variable as well as summary statistics can be found in Appendix B.

[18] This is also in the spirit of Banerjee et al. (2013) or Bursztyn et al. (2014).

where ϱ_i is an individual zero-mean error term distributed normally conditional on covariates, $\mathbf{v}_i$ is a vector of individual characteristics, and we use the same symbols for coefficients only for economy of notation and not to indicate equality across specifications. We report estimates in columns (6) and (7) of Table 2. Interestingly, we find that perceived past returns are related to the perceived share of financial circle peers who are informed or who participate in the stock market, but not to the corresponding features of the outer circle. This is consistent with our findings in the expectations regressions that did not control for perceived returns and with the introduction of such controls rendering the peer circles insignificant.

All in all, results in Table 2 paint a consistent picture: any influence of peers on subjective return expectations operates through altering perceptions of past returns. The finding that only the financial and not the outer social circle are related to perceptions of past returns also suggests that the observed relationship is unlikely to arise from unobserved heterogeneity, a conclusion that will be subjected to further scrutiny in what follows. This first set of results is strongly consistent with the presence of an information channel in peer influences running only through the financial circle and only through perceptions of what happened in the recent past. It also points to a novel role for friends and acquaintances in enabling respondents to process factual information (about past stock market outcomes) beyond findings in the literature on the importance of own cognitive ability for financial behavior.[19]

4.3. Stockholding. Our analysis of subjective stock market expectations above has confirmed our model's prediction that connectedness to people more knowledgeable about the stock market raises expected (excess) returns. Since expected returns are positively related to desired portfolio exposure to stocks, this alone would suffice to create a role for social interactions in stockholding decisions. In this section, however, we examine whether connectedness influences the prevalence of stockholding and the degree of exposure to stockholding risk beyond its effect through stock market expectations.

Our starting point is the demand for investing in the stock market in expression (9). Reorganizing this indicates that the risk-adjusted individual demands depend on a term that is common to all agents and a term that is individual-specific. Since we are exploiting empirically the variation across agents, a linearization of (9) suggests the following econometric specification for agent i's share of financial wealth invested in the stock market:

$$D_i = \%FW_i = \max\{0,\ \lambda_0 + \underset{(+)}{\lambda_1} k_i^* + \underset{(+)}{\lambda_2} Expec\ R_i + \underset{(-)}{\lambda_3} \rho_i + \boldsymbol{\tau}_i \boldsymbol{\lambda} + u_i\}, \tag{16}$$

where u_i is an individual-specific error term. The vector $\boldsymbol{\tau}_i$ contains individual characteristics for respondent i. The vector $\boldsymbol{\tau}_i$ contains the following controls: age, gender, marital status, number of children, geographical region, employment status, assets, income, borrowing, liquid savings.[20] The signs under the constant coefficients indicate the theoretically predicted signs: more relevant connections (with coefficient λ_1), a higher expected net excess return, $Expec\ R_i = (x_i - p)$, (λ_2) and lower risk aversion (λ_3) increase the desired fraction of financial wealth to be invested

[19] See, for example, Christelis et al. (2010), Grinblatt et al. (2011) and Hurd et al. (2011).

[20] The detailed definitions of these can be found in Appendix B.

in the stock market, controlling for individual characteristics.

The zero term within the specification allows for the observed prevalence of non-stockholders in the population. The empirical literature on stockholding has dealt with stock market non-participation in two ways. One way is discrete choice estimation (typically probit and less frequently logit regressions) of the decision whether to hold stocks or not. Non-participation arises when the expected benefit from participation, which is a function of desired stockholding and the expected equity premium, does not exceed the participation cost. A second type of empirical approach invokes tobit estimation of the risky portfolio share. This is typically linked to the portfolio model by considering that an agent can have a desired portfolio share that is positive or negative, but the latter is restricted to zero through a constraint preventing short sales of stock. This offers a possibility to examine the household's degree of exposure to stockholding risk, as opposed to focusing only on its presence.[21] Note that, in both cases, portfolio demand, stock market expectations, and stock market perceptions play a potentially important role.

By analogy to our analysis of expectations and perceptions above, we also consider another specification involving behavior among peers. This takes the form:

$$D_i = \%FW = \max\{0,\ \zeta_0 + \zeta_1 D_i^e \underset{(+)}{+\zeta_2}\, Expec\ R_i + \underset{(-)}{\zeta_3}\, \rho_i + \boldsymbol{\tau}_i \boldsymbol{\zeta} + w_i\}. \tag{17}$$

where D_i^e represents a feature of the respondent's social circle, in this case the extent of participation in the stock market, as perceived by the respondent.

Consistent with our approach in the previous section, we split the respondent's social circle into the financial circle and the outer circle, and we use the respondent's perceptions about both. In specification (16) we focus on the respondent's perceptions about how informed the two circles are with regard to the stock market; and in (17) we use their perceptions regarding stock market participation of the two circles.

Stock Market Participation. Column (1) of Table 3 presents results for a participation probit that employs responses on how informed the two circles are. We confirm that subjective expected returns are positively and significantly related to participation, consistent with existing portfolio models, even after controlling for a number of household characteristics and for its declared willingness to take risks, formulated as absolute risk aversion. Interestingly, however, we find an effect of how informed the financial circle is perceived to be, which is positive and statistically significant. Although a perception that the financial circle is informed about the stock market is positively related to the probability that the respondent participates in the stock market, the same is not true of the outer circle. A plausible mechanism that gives rise to this finding is that respondents are more likely to participate in the stock market if they think that the people with whom they discuss financial matters have the necessary information to engage in fruitful interactions regarding the stock market that extend beyond expected returns

[21] This standard approach should be interpreted with some caution, as it reduces stock market non-participants to frustrated short-sellers of stock. Nevertheless, it is consistent with the use of an estimator for censored data such as tobit and opens up possibilities for studying the extensive margin.

and past returns.

Column (2) repeats the exercise but now uses respondent perceptions as to the prevalence of stock market participation in the financial and in the outer circle. Here the potential for imitation of stock market participation among peers is clearly present. Imitation of a person whom the respondent considers worthy of discussing financial matters is likely to be mindful imitation. It might even not be imitation at all, if the respondent is not influenced by the mere fact that the members of the financial circle participate in the stock market, but by the information they are able to provide because they do participate.

However, we also find that stock market participation among the outer circle has a positive and statistically significant relationship to the respondent's own decision to hold stocks. As respondents do not discuss financial matters with these members of their social circle, being influenced (positively) by the share of participants in that outer circle suggests imitation. The finding that respondents are influenced by the participation of people in their social circle whom they do not consider suitable for discussing financial matters with them indicates that a tendency for conformism and mindless imitation as regards stock market participation cannot be ruled out. This tendency appears to stand side by side with a considerable tendency of respondents to be influenced only by their financial circle when it comes to forming perceptions about past returns, expectations about future returns, and decisions based on the informative value of social interactions.

Columns (3) and (4) pursue further the econometric problem of potential unobserved heterogeneity creating the observed correlations. In both cases, it is possible that the observed relationships arise from unobserved factors that influence both the respondent and the respondent's peers. Splitting the social circle into financial and outer circles already provides evidence against unobserved heterogeneity, but now we have in column (2) a case in which we observe the joint significance of both circles. In columns (3) and (4), we reshuffle the responses regarding how informed the two circles are and how heavily they participate in the stock market, respectively. Ideally, we would like to do this reshuffling among the actual peers of each respondent. As the identity of the peers is unknown to us and the peers may not be included in the data set, we reshuffle responses among members of the same age and education group and living in the same region (department) as the original respondent, on the assumption that these are key criteria determining the social circle. We find that, when each respondent is matched not with his or her own responses regarding the financial and outer circles, but with those of a random person in the same age and education group and living in the same area, the coefficients on both circles are no longer statistically significant. This shows that the observed correlations in columns (1) and (2) do not arise from unobserved factors that affect all members of the same age and education group who reside in the same area, including the respondent.

Conditional portfolio shares. Columns (5) and (6) of Table 3 adopt a tobit specification in order to test for peer influences on the size of the exposure to stockholding risk in the portfolio. Symmetrically to columns (1) and (2), columns (5) and (6) examine the role of perceptions regarding how informed the two circles are and to what extent they participate in the stock market. Here, the result is the same, regardless of which feature of the peer circle we consider: once we control for subjective expected returns, neither the financial nor the outer social circle exert an influence on the extent of exposure to stockholding risk, at least through how informed and how engaged in stockholding they are.

All in all, the results in Table 4 suggest that peers do influence stock market participation and exposure to stockholding risk to the extent that they influence subjective stock market expectations, but we do not find any further effect on the size of the portfolio share devoted to stocks given that the respondent participates at all. While exchange of useful information and possibly mindful imitation do seem to influence whether people participate in the stock market or not, we also find a potential for mindless imitation of the outer circle with regard to the stock market participation decision.

Robustness. So far, we have subjected our findings of a relationship between peer information/peer participation and respondent behavior to the scrutiny of distinguishing between the inner (financial) circle and the outer social circle, as well as of running placebo tests as ways to handle unobserved heterogeneity. Here we examine robustness of our findings to recognizing that respondents have a choice of whether to form a financial circle or not, and that this choice may be taken jointly with the decision regarding stockholding. Specifically, it may be that people have some unobserved reason to hold stocks and this factor also pushes them to form a financial circle with whom they can discuss stockholding and other financial matters. This joint decision could induce the observed correlation between stockholding and financial sector attributes without any implication of causality from the financial circle to the respondent's stockholding behavior.

To deal with this issue, we follow Blume et al. (2011) and we treat group choice and behavior within a group as a set of joint outcomes. Specifically, we consider a bivariate probit model for the choice to participate in the stock market and the choice to form a financial circle, allowing for correlated unobserved factors influencing the two choices.[22] We estimate the following bivariate probit econometric specification:

$$\begin{cases} \Pr(Stocks_i > 0) = \Phi(\lambda_0 + \lambda_1 k^*_{iFC} + \lambda_2 k^*_{iOC} + \lambda_3 Expec\ R_i + \lambda_4 \rho_i + \boldsymbol{\tau}_i \boldsymbol{\lambda}) \\ \Pr(FC_i > 0) = \Phi(\nu_1 k^*_{iSC} + \nu'_2 Expec\ R_i + \nu'_3 \rho_i + \boldsymbol{\tau}_i \boldsymbol{\nu}') \end{cases} \tag{18}$$

and the corresponding one for peer participation in stockholding as opposed to the share of informed peers, where we replace k^* with D^e. The stockholding participation probit is modeled as in previous sections. For the probit describing whether the respondent decides to form a financial circle as a subset of the social circle, we postulate a set of explanatory variables that include the respondent's observable characteristics, the elicited degree of absolute risk aversion, subjective expectations regarding stock market returns, and subjective perceptions about the share of members of the overall social circle that is informed about the stock market and the share that is participating in the stock market.

[22] Note that a two-step process, with financial circle formation as the first step, would run into the difficulty that having a financial circle is not a prerequisite for holding stocks. Indeed, our data include stockholders who do not declare having a financial circle.

In principle, perceptions about the social circle could have ambiguous effects on the decision to form a financial circle. Perceiving more social contacts as informed or participating (or both) could encourage the respondent to discuss financial matters with some of them or could lead the respondent to avoid restricting communication about financial matters to a subset of the social circle. However, the more being in the financial circle and discussing financial matters with the respondent has to do with exchanging information rather than engaging in mindless imitation, the more likely it is that we will observe a particular pattern. Specifically, in the case of informative social interactions rather than mindless imitation, we would expect to find that respondents are more likely to form a financial circle when they perceive their social circle to have a larger share of informed peers; and that they are not influenced in this decision by the share of people they perceive as candidates for imitation.

Table 4 presents two bivariate probits, one using the share of the social circle perceived to be informed, and the other focusing on the share perceived as participating. Columns (1) and (3) are the stock market participation branches of the corresponding bivariate probits, while columns (2) and (4) are the branches depicting the choice of whether to form a financial circle or not. The stock market participation branches in both cases confirm the results we obtained earlier, now that we also allow for a unobserved correlation in the two decisions: subjective expected returns are positively correlated with stock market participation, and so are the perceived shares of informed members in the financial circle, as well as of the participating members in the financial or outer circles. This shows robustness of our earlier results to the new specification. The estimates for the corresponding second branches, though, provide additional support for the presence of informative social interactions: the share of informed members of the social circle is statistically significant for the choice to form a financial circle, but the mere share of participating members is not.

Moreover, Table 4 sheds light on the main concern leading to the bivariate probit specification, namely that respondents who intend to invest in the stock market, choose within their social circles, the peers with whom to discuss their own financial matters. In that case, the error terms u_i and ν_{iFC} would be correlated, $u_i = \rho\nu_{iFC} + \upsilon_i$, and the results reported in previous tables would be biased due to selection. The last three rows in Table 4 report ρ and the Wald test statistics and associated p-values for different specifications of (18) considered, and in no case can we reject the null of independence, $H_0 : \rho = 0$. In addition, estimated coefficients on the peer variables and on other covariates tend to be similar to those in Table 3.

The robustness of our findings to explicit consideration of the joint decision to have a financial circle and to hold stocks may admit an intuitive interpretation, also in light of Blume et al. (2011, 2015): by conditioning on the share of peers informed or participating with whom the respondent does not exchange on own financial matters (i.e. on the outer social circle information or behavior), we are implicitly controlling for the possibility of selection into the financial circle in specifications considered in previous sections.

All in all, bivariate probit analysis provides a useful robustness check for our earlier findings and some additional support for the hypothesis that social interactions regarding stockholding have an important information rather than mere imitation content.

4.4. Comparison to experimental evidence. Banerjee et al. (2013) and Bursztyn et al. (2014) adopt experimental methods to disentangle information from imitation effects of the social circle. Banerjee et al. (2013) consider a novel microfinance program and replace the unconditional individual probability of participation by the individual probability of participation conditional on individual information sourced from friends. Once informed, they find that an agent's decision to participate in the program is not significantly influenced by the fraction of her friends participating, concluding that the influence of peer participation is mainly an information effect.[23] It is possible to construct an extreme interpretation of their findings that would be in conflict with ours. Under such an interpretation, if people are generally aware of the existence of stocks, they should no longer be influenced by the share of their peers participating in them. Such an interpretation would be in contrast to our findings.

We opt for a different interpretation, which stresses the nature of the underlying financial product. The particular microfinance product may have a much higher probability of participation conditional on awareness than stocks do. To take an extreme, if practically all people who know about the microfinance product choose to use it, the value of social links is in transmitting otherwise inaccessible information and providing more information has no further effects. Yet we know that stock market participation is quite limited even among the many people aware of stocks in developed economies. Thus, there is room for further information beyond the existence of stocks to deliver effects on stock market participation and on the degree of exposure to stockholding risk.

Bursztyn et al. (2014) adopt a different experimental strategy and find empirical support for both information and imitation channels. They design a field experiment amongst socially paired investors of a Brazilian brokerage firm, and through sequential randomization, they separate the effect of a social peer actually purchasing a new financial product from being informed about it. This is accomplished by randomly informing peers about products but also controlling whether they are able to invest in them or not. They are thus able to decompose the total effect of observing a peer hold a product into one that comes from the information that the product exists and one that comes from the information that a known product has been purchased by the socially connected peer. Naturally, being able to measure these effects requires focusing on products that are completely unknown to respondents at the start of the experiment and having full control of information flows and acquisition possibilities.

In our analysis, we deal with a well-known, yet information-intensive product in a developed economy, namely stocks in France. Our econometric results, based on newly designed and produced survey data, point to an information role for social interactions, as effects are obtained only through interactions with the financial but not with the outer circle. However, we have also found that stock market participation (as opposed to the degree of exposure) is also subject to imitation of the outer circle, with whom no discussion of financial matters takes place. The more limited role for mindless imitation in the context of a widely known and mature product such as stocks is quite intuitive: not much information is added by learning that an extra person

[23] Their work relies heavily both on the identification of the actual network structure and on control over the information spreading through it.

holds it, compared to learning this about a completely novel product.

Mature financial products for which there is limited participation and uncontrolled access to information by potential investors abound in developed economies. Population-wide surveys of behavior relating to such products can provide useful additional insights to the interesting findings of tightly managed experiments with new or artificial financial products.

5. Conclusions

We provide a model where purely informative social interactions influence subjective expectations of future stock market returns and demand for investing in stocks. The model shows that, conditional on investing, an agent collects more information from better informed peers, and thus invests in stocks more aggressively. By designing, collecting, and exploiting novel survey data for a representative sample of the French population by age, wealth and asset classes, collected in December 2014 and May 2015, we find strong support for the presence of informative social interactions.

Based on our findings, the extent to which the respondent's financial circle is informed about the stock market, as well as the extent to which it participates in it, tend to influence perceptions of recent stock returns and, only through them, expectations of future returns. Stock market participation and the degree of exposure to stocks conditional on participation are positively influenced by stock market expectations. However, this is not the only channel through which peers influence stockholding behavior. Even controlling for subjective expectations, stock market participation and the conditional portfolio share are positively influenced by the extent to which the financial circle is informed or participating. We did not find evidence that the corresponding attributes of the outer social circle, with whom the respondent does not discuss finances, influence perceptions of past stock returns, expectations of future returns or the portfolio share of stocks conditional on participation in them. These findings are consistent with the notion that social interactions tend to be informative as regards stockholding. However, we did find some evidence for the presence of imitation of stock market participation observed in the outer social circle. Unlike what happens with the financial circle, respondents do not discuss financial matters with members of this outer circle, and this creates a presumption for the presence of mindless imitation in the participation decision alongside informative social interactions.

We have followed a three-pronged approach to dealing with unobserved heterogeneity being the source of these results. First, we distinguish between attributes of the financial and of the outer circle: unobserved heterogeneity would tend to make both relevant rather than only one. Second, we perform placebo tests, where respondents' perceptions regarding the financial and the outer circle are reshuffled across respondents of the same age, education, and region (department). We find that such reshuffling eliminates the estimated effects. Third, we adopt a bivariate probit specification which recognizes the possibly joint nature of the decision to hold stocks and to form a financial circle. When we treat group choice and behavior within a group as a set of joint outcomes, the null of independence among the two choices fails to be rejected in our sample, and our estimates tend to be similar regardless of whether we allow for a joint decision or consider stockholding choices separately. As a further robustness exercise, we use four questions from the TNS2015 questionnaire (questions C5, D6, D7 and D8) that ask respondents to report how they perceive themselves relative to those in their social and financial circles, in terms of professional standing, value of their financial assets and qualifications. For all these questions, respondents answered that less than half of their acquaintances were similar to them in terms of qualifications and professional standing, or had more or less the same assets as them. This cross check provides some evidence against strong homophily, thus lending more support to our model-backed interpretation of the estimated effects.

Informative social interactions imply a potentially powerful channel through which financial information and financial literacy can permeate through the economy, even if the original information or financial education content reaches a relatively small segment of the population. They point to a social multiplier in financial education or financial information even in countries with advanced financial development and in products that are mature and widely known. They provide a (partial or superior) substitute for financial advice that is ill-conceived, poorly incentivized, or hardly trusted. Finally, they are likely to grow in importance, as use of social media and the potential to reach more people with new information spread rapidly. Yet the data also indicate the presence of mindless imitation in the stock market participation decision. This, along with the inequities involved in having to rely on second-hand information, suggest caution in relying exclusively on social interactions for the spread of useful information and best financial practices.

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A. Noisy Rational Expectations Equilibrium

We conjecture that the risky asset price has the form

$$p = \pi_0 + \sum_{j=1}^{n} \pi_j x_j - \gamma Z_n. \tag{19}$$

and imposing market clearing .

$$\sum_i D_i^* = Z_n$$

Next, we make some notational assumptions. Let $\mathbf{S} \equiv Cov\left(R\boldsymbol{\epsilon}\right) = R\Sigma R^T$ so that $R = K^{-1}G = K^{-1}A\Sigma^{-1}$, where K is a diagonal matrix with diagonal elements the sums of the rows of G, i.e. the strengths of the nodes, $K = diag\left[k_1, ..., k_n\right]$, and therefore

$$\mathbf{S} \equiv K^{-1}WK^{-1}.$$

where the matrix W is defined by $W = G\Sigma G^T = A\Sigma^{-1}A$. We note that because A is symmetric and $a_{ij} \in \{0, 1\}$, it is trivially true that $W_{ii} = k_i = \sum_{j=1}^{n} a_{ij}/s_j^2$.

Finally we make the following assumptions:

A1. $\|W\|_\infty = o\left(n\right)$, i.e.

$$\lim_{n\to\infty} \frac{\|W\|_\infty}{n} = 0 \tag{20}$$

A2. $\lim_{n\to\infty} \frac{1}{n} \sum_{i=1}^{n} \frac{k_i}{\rho_i} = \beta + o\left(1\right)$. This is slightly modified version of the assumption made by Ozsoylev and Walden (2011). It is written in terms of k_i, i.e. the strength of links, *weighted by the risk aversions*, but has the same interpretation as in Ozsoylev and Walden (2011), i.e. that the average strength of nodes weighted by risk aversion (average risk-adjusted connectedness) is β, and is finite.

A3. The risk aversion coefficients come from a distribution such that the harmonic mean is finite as $n \to \infty$, i.e.

$$\lim_{n\to\infty} \frac{n}{\sum_{i=1}^{n} \frac{1}{\rho_i}} = \hat{\rho} < \infty.$$

A4. The limit

$$\lim_{n\to\infty} k_i = k_i^* < \infty$$

exists and is finite. The interpretation of this assumption is that no investor can be a node with very large strength as the network becomes larger. In other words, no agent can have too many connections that have very precise signals. This excludes scenarios of an informationally superior elite in the network.

Under these assumptions can extend Ozsoylev and Walden's results to the following:

Theorem 1. *Under Assumptions A1-A4, with probability 1, the equilibrium asset price converges to*

$$p = \pi_0^* + \pi^* \bar{X} - \gamma^* \bar{Z}$$

where

$$\begin{aligned} A &= \frac{\beta}{\hat{\rho}\Delta^2} \\ \pi_0^* &= \gamma^* \left(\frac{\bar{X}\Delta^2 + \bar{Z}\beta\sigma^2}{\sigma^2\hat{\rho}\Delta^2 + \sigma^2\beta} \right) \\ \gamma^* &= \frac{\sigma^2\hat{\rho}\Delta^2 + \beta\sigma^2}{\beta\sigma^2\hat{\rho}\Delta^2 + \Delta^2 + \beta^2\sigma^2} \\ \pi^* &= \gamma^*\beta \end{aligned}$$

and the optimal demand for the risky asset for an investor i is

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

The proof follows the same steps as in Ozsoylev and Walden with some suitable modifications. The strategy of the proof is to follow the 'guess-and-verify' approach, and the main steps are:

1. Conjecture a functional (linear) form for the price, with unknown coefficients.
2. Derive beliefs for the agents as a function of the price coefficients (using Bayesian updating).
3. Derive the optimal demands for the agents given their endogenous beliefs.
4. Impose market clearing and solve for the stock price.
5. Impose rational expectations (i.e. equalize coefficients) and confirm that the corresponding system of equation generates a solution, which will then provide solutions for the price coefficients.
6. Check, with asymptotic arguments that conditions required to ensure that the coefficients exist (i.e. the system has solution) as $n \to \infty$, are satisfied given the assumptions A1-A4.

The detailed steps of the proof are available upon request.

B. Definitions of Variables

Table 5 reports summary sample statistics for all the variables we have used for the analysis.

B.1. Expec. R. and Perc. R.: Subjective Mean Expectations and Mean Perceptions of Stock Market Returns. To measure expectations, we elicited probabilistically respondents' beliefs about the cumulative stock market (CAC-40 index) return over a five-year horizon, P_{t+5}, relative to December 2014, P_t, from the following question (translated wording):

C39: 'In five years from now, do you think that the stock market... ' (For each category write down how likely the occurrence is by assigning a value between 0 and 100. The sum of all your answers must be equal to 100):

... will have increased by more than 25%

... will have increased by 10 to 25%

... will have increased by less than 10%

... will be the same

... will have decreased by less than 10%

... will have decreased by 10 to 25%

... will have decreased by more than 25%

Question C39 inquires respondent i about the subjective relative likelihood of occurrence, $p^i_{t+1,k}$, of each of the seven alternative scenarios, $k = 1, ..., 7$. Each scenario represents a possible outcome range for the index percentage change between t and $t+5$, $R_{t+1}(5) \equiv \frac{P_{t+5}}{P_t} - 1$.[24] Questions C40 and C41 provide subjective upper and lower bounds for the percentage change, $R^i_{\max}$ and $R^i_{\min}$ respectively. The corresponding outcome ranges are:

$$R_{t+1} \in \left\{ \underbrace{[-R^i_{\min}, -0.25)}_{k=1}, \underbrace{[-0.25, -0.10]}_{k=2}, \underbrace{(-0.10, 0)}_{k=3}, \underbrace{\{0\}}_{k=4}, \underbrace{(0, 0.10)}_{k=5}, \underbrace{[0.10, 0.25]}_{k=6}, \underbrace{(0.25, R^i_{\max}]}_{k=7} \right\}$$

and respondents' subjective likelihoods are accordingly:

$$p^i_{t+1,k} \equiv \Pr{}^i \left[R_{t+1} \in k\right] = \Pr{}^i [\frac{P_{t+5}}{P_t} - 1 \in k], \forall i$$

and zero elsewhere, i.e. $R_{t+1} \in (-\infty, -R^i_{\min}) \cup (R^i_{\max}, +\infty)$. Table 5 reports summary sample statistics for respondents' answers regarding expectations about stock market returns, imposing a uniform distribution within the different outcome ranges. On average, households appear more pessimistic and uncertain than the historical record would predict.

To quantitatively assess how factually informed respondents are, we elicit probabilistically respondents' perceptions about the most recent cumulative stock market return (CAC-40 index) over the three years, P_{t-3}, immediately prior to fielding the survey (December 2014), P_t, as follows (translated wording):

[24] We follow the standard convention in finance for long-horizon returns, and let $1 + R_{t+1}(s)$ denote the stock market index gross return over *s periods ahead* (hence the subindex $t+1$), which is equal to the product of the s single-period (or yearly) returns:

$$1 + R_{t+1}(s) = \prod_{f=0}^{s-1} (1 + R_{t+1+f}) = \prod_{f=0}^{s-1} \left(\frac{I_{t+1+f}}{I_{t+f}} \right)$$

Similarly, we let $1 + R_t(s)$ denote the stock market index gross return *over the most recent* s periods from date $t - s$ to date t (hence the subindex t):

$$1 + R_t(s) = \prod_{b=0}^{s-1} (1 + R_{t-b}) = \prod_{b=0}^{s-1} \left(\frac{I_{t-b}}{I_{t-1-b}} \right)$$

See Campbell *et al.* (1997) for details.

C42: 'Over the last three years, do you think that the stock market... (For each category write down how likely the occurrence is by assigning a value between 0 and 100. The sum of all your answers must be equal to 100):

... has increased by more than 25%

... has increased by 10 to 25%

... has increased by less than 10%

... has remained the same

... has decreased by less than 10%

... has decreased by 10 to 25%

... has decreased by more than 25%

Similarly to Question C39, Question C42 inquires household i about the subjective relative likelihood of occurrence, $p^i_{t,k}$, of each of the seven alternative scenarios, $k = 1, ..., 7$. Each scenario represents a possible outcome range for the percentage change in the index between $t - 3$ and t, $R_t(3) \equiv \frac{P_t}{P_{t-3}} - 1$. Probabilistic elicitation of realized outcomes thus enables us to measure how uncertain they are when conveying their answers. Since ranges $k = 1$ and $k = 7$ are unbounded, we set $(R_{\max}, R_{\min})$ to match observed values. The outcome ranges for R_t are identical to those of question C39. Accordingly, households' subjective likelihoods are given by:

$$p^i_{t,k} \equiv \Pr^i \left[R_t \in k\right] = \Pr^i \left[\frac{P_t}{P_{t-3}} - 1 \in k\right], \forall i$$

Three years prior to the time when the survey was conducted (December 2011), the stock market index was only slightly above the floors reached after the dot-com and Lehman Brothers busts. But, between late December 2011 (CAC 40 = 3159.81) and late December 2014 (CAC 40 = 4252.29), the index had increased an overall 34.57%. Figure 1 in the main text shows the time window chosen within the wanderings of the CAC-40 index between 1990 and 2016. Table 5 reports summary sample statistics for respondents' answers regarding perceptions and beliefs about stock market returns, imposing a uniform distribution within the different outcome ranges. A striking finding is that households are on average also pessimistic regarding the most recently realized three-year cumulative stock market return (Dec. 2011-Dec. 2014). Although this might be due to imperfect recall given the unusually long horizon, it might also be related to the 2007 Lehman Brothers' bust being overweighted on respondents' memory (Hurd et al., 2011), even if outside the question's time window. The big spread around the realized three-year cumulative stock market perceived return came as no surprise, and it captures factual ambiguity. In addition, it is remarkable that it remains smaller than the spread around the expected five-year ahead cumulative stock market return.

Figures B1a and B1b below report the histograms of respondents' answers to the subjective expectations and perceptions questions, C39 and C42 respectively, for both the mean (left panel) and the standard deviation of mean responses (right panel). Figure B1a (right panel) conveys that around 34% of respondents reported a zero standard deviation of subjective mean expected returns for the five-year ahead stock market cumulative return, in clear dissonance with available historical evidence. This misperception of stock market risk motivates the definition of a categorical variable 'Certain Expec. R.', which takes value 1 if the respondent reports a zero standard deviation of mean expected returns, and takes value 0 otherwise.

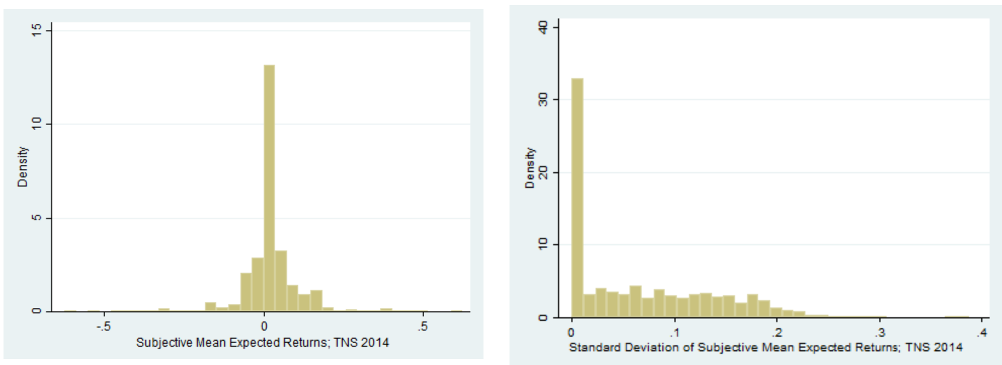

Figure B1a:
Histograms of the subjective mean (left panel) expected five-year ahead cumulative return, and its standard deviation (right panel); TNS2014.

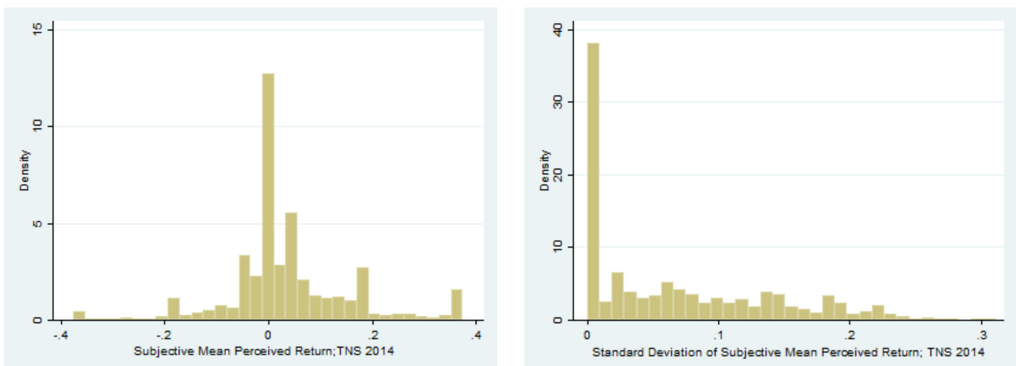

Figure B1b:
Histograms of the subjective mean (left panel) perceived three-year cumulative realized return, and its standard deviation (right panel); TNS2014.

Arrondel et al. (2014) report that categorical answers to frequency, variety and access specialized media, advice from professionals, as well as the number of stock market transactions carried over the last year, increase the likelihood of being factually informed. Interestingly, parents' stock ownership status ('cultural transmission'), parents' educational attainment or family background do not increase the odds of being factually informed, and actually significantly decreases them for those who follow family advice. Since those who follow friends' advice are more likely to be informed, they interpret the evidence as being consistent with social interactions being instrumental in gathering information (Hong et al., 2004). On the other hand, a measure of optimism ('being lucky in life') has a negative impact on being informed, indicating that an 'overconfidence bias' is not present once gender is conditioned upon: although males appear better informed, supporting more optimistic forward looking expectations, optimists appear consistently worse informed. On the basis of that finding, they argue that Bilias et al.'s (2010) findings, consistent with inertia in households' portfolios, can be reconciled with Guiso and Jappelli's (2006) findings, consistent with excess trading even amongst the general population. Importantly, they do not find evidence of temporal or risk preferences determining information sets, in line with Van Nieuwerburgh and Veldkamp (2010). In addition, and although total wealth does not increase the odds of being informed, income does, in line with a costly information acquisition interpretation (Peress, 2004). Finally, they report that optimists and low income/income constrained respondents are less likely to be informed, consistent with rational inattention theory (Sims, 2003). Overall, those findings support probabilistically elicited perceptions as a sensible measure of factual information.

B.2. %FW: *Share of financial wealth invested in the stock market.* Respondents report their total financial wealth and the share of their total financial wealth invested in the stock market, in questions C16 and C19 respectively (TNS2014). Question C16 asks respondents to report their total financial wealth (excluding housing and own businesses) within given brackets (see below for further details). The translated wording for question C19 is:

C19: Approximately what percentage of your total financial wealth have you invested in listed or unlisted shares, directly or in unit trusts, in a personal equity plan or a mutual fund (yourself or a member of your household)? If you don't have any, please answer 0%.

We have a total of 2,891 observations for these questions. Out of 3,780 survey respondents, about 76% responded meaningfully. The mean percentage of financial wealth invested in the stock market is 5.32%, and the standard deviation is 14.52%.

B.3. Social and financial interactions. Summary statistics for questions C1, D1, C7 and D16 are presented in Table 5.

B.4. Demographics and other control Variables.

Endowments.

Total wealth: In the survey (question C29), the respondent is asked which of the ten predefined available brackets corresponds to the household's non-human wealth, including housing, estates and professional assets (without excluding debt):[25] 'Less than 8,000', 'between 8,000 and 14,999', 'between 15,000 and 39,999', 'between 40,000 and 74,999', 'between 75,000

[25] If we were interested in a continuous measure, we would implement the method of simulated residuals (Gourieroux et al. 1987). We would then regress an ordered probit of the respondents' total wealth (bracket) on demographic and socio-economic household characteristics. Once we would have the estimated total wealth, a normally distributed error would be added. We would then check if the value

and 149,999', 'between 150,000 and 224,999', 'between 225,000 and 299,999', 'between 300,000 and 449,999', 'between 450,000 and 749,999' and '750,000 or more'. Total wealth is given in Euros. From the empirical distribution we obtain total wealth quartiles, the bounds of which are given by '74,999', '224,999' and '449,999'. The reference category is the first quartile, 'less than 74,999'.

Total financial wealth: In the survey (question C16), the respondent is asked which of the ten predefined available brackets corresponds to the household's financial wealth (excluding housing, estates and professional assets), including cash and positive balances on checking accounts: 'Less than 500', 'between 1,500 and 2,999', 'between 3,000 and 7,999', 'between 8,000 and 14,999', 'between 15,000 and 29,999', 'between 30,000 and 44,999', 'between 45,000 and 74,999', 'between 75,000 and 149,999', 'between 150,000 and 249,999' and '250,000 or more'. Total financial wealth is given in Euros.

Income: For the income of the household, the survey (question A12) asks the respondent which of the nine predefined available brackets better corresponds to her situation: 'Less than 8,000', 'between 8,000 and 11,999', 'between 12,000 and 15,999', 'between 16,000 and 19,999', 'between 20,000 and 29,999', 'between 30,000 and 39,999', 'between 40,000 and 59,999', '60,000 or more' and 'No income'. Income refers to the respondent's annual income (earnings, pensions, bonuses, etc.) in Euros, net of social contributions but before personal income taxes.[26] In addition, TNS reports also the net gross monthly income of the household, in Euros. From the empirical distribution, we obtain the income quartiles the bounds of which are given by '11,999', '19,999' and '29,999'. The reference category is the first quartile, 'less than 11,999'.

Occupational status: (of the household head) the TNS 2014 survey asks respondents about their occupation, grouped into five categories: 'inactive'; 'unemployed'; 'employed' which includes 'white-collar' (liberal and managerial employees) and 'blue-collar' workers (employees, clerical and manual workers); 'self-employed' which includes farmers, artisans and shop and business owners, and 'retired'. Finally, we group the first two categories into one, the reference category.

Preferences.

Absolute risk aversion: The following question is asked to the respondent: 'If someone suggests that you make an investment, $\widetilde{S}_i$, whereby you have one chance out of two win 5000 euros and one chance out of two of losing the capital invested, how much (as a maximum) will you invest?' The question aims at eliciting the taste for risk from each respondent i, with

falls inside the bracket originally chosen by the individual. If not, another normal error would be added and so on until we the true interval is correctly predicted. Doing so would allow us to overcome the non-response problem for some households. Would there be a missing value, the predicted value plus a normal error would be directly used.

[26] In France, income is not taxed at the source.

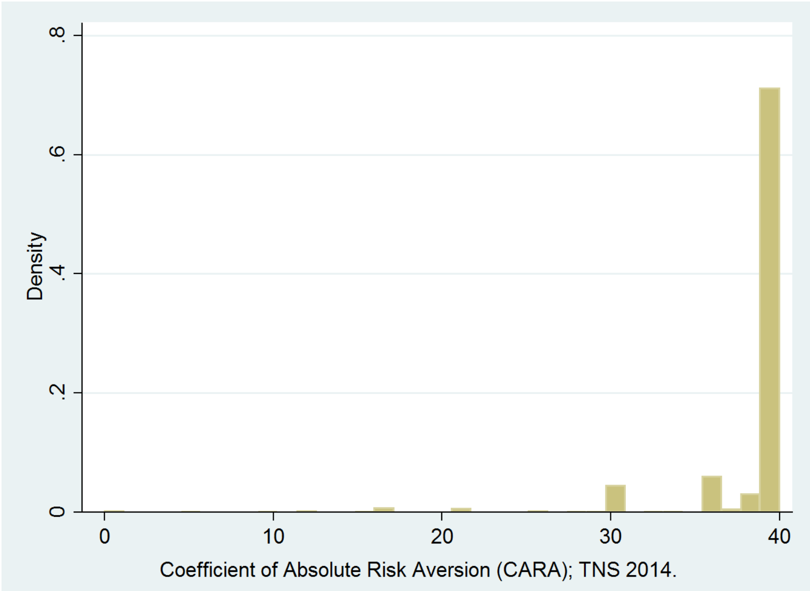

Figure 2: Histogram of responses to the hypothetical lottery that enables elicitation of the respondent's coefficient of absolute risk aversion (CARA) -TNS 2014 survey question C44.

preferences $u^i(.)$, from the following equality:

$$u^i(w_i) = \frac{1}{2}u^i(w_i+5,000)+\frac{1}{2}u^i(w_i-Z_i) \equiv Eu^i(w_i+\widetilde{S}_i)$$

The coefficient of absolute risk aversion can be then obtained from a second order Taylor expansion, as $A_i(w_i) = 2(5000 - Z_i)/(5000^2+Z_i^2)$, where Z_i is the amount that the respondent declares to be willing to invest. Those who declare $Z_i< 5000$ are risk-averse $Z_i= 5000$, are risk-neutral and $Z_i> 5000$ are risk-lovers. The outcome range for the coefficient of absolute risk aversion $A_i(w_i)$ is $[0, 40]$. 3,335 respondents answered the question, with a mean response of 38.40 and a median value of 39.92. Fig. **??** displays the histogram of responses, which is very skewed to the left but remains within the range responses found in the literature. Further details regarding the measure of absolute risk aversion can be found in Guiso and Paiella's (2008) work.

Demographics.

Age: it is a continuous variable equal to the age of the household head. Respondents' age range is in between 19 and 94. We group respondents into four categories: 'younger than 35', 'between 35 and 49 years old', 'between 50 and 64 years old' or 'older than 65'. Depending on the age bracket within which respondents' age falls, it takes value 1 within it and zero otherwise.

Gender: it is a dummy variable equal to 1 if the household head is a male, and is equal to 0, if a female.

Marital status: Marital status is based on current legal marital status. Respondents who are married or/and living with a partner are coded as 1, and 0 otherwise.

Children at home: it is a dummy variable coded as 1 if the respondent replies that there is (a positive number of) children living at home with their parent(s), and is coded as 0 otherwise.

Constraints.

Liquidity and borrowing constrained: Respondents are asked if they held an outstanding (negative) debt balance, and if not, why. We then constructed a dummy variable that takes value 1 if the respondent answers the question in the categories 'because my debt application was turned down' or 'because I did not submit an application for fear of being turned down', and value 0 otherwise.

Saving: Question C73 in the TNS 2014 survey asks the respondent about total net household saving over the last 12 months. Six brackets are provided, in Euros, of which the first is zero ('we have not saved'). Around 31% of respondents report no savings over the last 12 months. From the empirical distribution, we obtain the saving quartiles the bounds of which are given by '0', '999' and '4,999'. The reference category is the first quartile.

Region of residence is a categorical variable, with nine possible categories representing the respondent's region of residence: 'reg 1' is Paris, 'reg 2' is 'Nord', 'reg 3' is 'Est', 'reg 4' is 'BP Est', 'reg 5' is 'BP Ouest', 'reg 6' is 'Ouest', 'reg 7' is 'Sud Ouest', 'reg 8' is'Sud Est' and 'reg 9' is 'Mediterranée'.

Information.

Education is a captured by a single categorical variable which takes value 1 if the respondent completed college or a diploma above (BAs, BScs, MScs, MBAs, professional certifications, PhDs and postdoctoral students), and takes value zero otherwise, i.e. High school or less (primary and secondary) and if the respondent failed to complete college education (technical degrees beyond high school but below college, including professional and vocational degrees).

C. Tables

Full tables with all the demographic and socio-economic controls are available from the authors upon request.

TABLE 1: Abbreviations and notation

Abbreviation	Stands for	Questions	From
SC	Social circle	C1	TNS2015
FC	Financial circle	D1	TNS2015
OC	Outer circle	C1, D1	TNS2015
$\%SC\ Inform.$	Perceived share of SC members informed about stock market	C7ii	TNS2015
$\%SC\ Particip.$	Perceived share of SC members investing the stock market	C7i	TNS2015
$\%FC\ Inform.$	Perceived share of FC members informed about stock market	D16ii	TNS2015
$\%FC\ Particip.$	Perceived share of SC members investing in stock market	D16i	TNS2015
$\%OC\ Inform.$	Perceived share of OC members informed about stock market	C1, D1, C7ii/D16ii	TNS2015
$\%OC\ Particip.$	Perceived share of OC members investing in stock market	C1, D1, C7i/D16i	TNS2015
$\%FW$	Share of financial wealth invested in the stock market	C19	TNS2014
$Pr(stocks > 0)$	Probability of holding stocks (directly and/or indirectly)	C19, C3	TNS2014
$Perc.\ R$	Perceived mean realized stock market returns	C42	TNS2014
$Expec.\ R$	Subjective mean expected stock market returns	C39	TNS2014

TABLE 2: Expectations and perceptions

VARIABLES	(1) *Expec.R*	(2) *Expec.R*	(3) *Expec.R*	(4) *Expec.R*	(5) *Expec.R*	(6) *Perc.R*	(7) *Perc.R*
%FC Inform.	0.000239*			5.88e-05		0.000678***	
	(0.000140)			(0.000135)		(0.000221)	
%OC Inform.	4.18e-05			3.86e-05		-4.55e-06	
	(0.000268)			(0.000242)		(0.000371)	
%FC Particip.		0.000225*			7.93e-05		0.000544***
		(0.000129)			(0.000124)		(0.000211)
%OC Particip.		0.000117			-1.64e-05		0.000636
		(0.000360)			(0.000340)		(0.000462)
Perc. R			0.286***	0.285***	0.284***		
			(0.0266)	(0.0267)	(0.0266)		
Risk aversion	-0.000683*	-0.000688*	-0.000358	-0.000337	-0.000336	-0.00136**	-0.00139**
	(0.000385)	(0.000385)	(0.000339)	(0.000341)	(0.000341)	(0.000580)	(0.000577)
Controls	yes	yes	yes	yes	yes	yes	yes
Observations	2,535	2,535	2,535	2,535	2,535	2,255	2,255
F	2.996	3.025	6.226	5.610	5.543	5.059	5.121

Notes: Regressions on share of financial and outer circles informed about or participating in the stock market. In all regressions we control for household characteristics (age, gender, marital status, number of children, education, region of residence, employment, income, savings). Dummies for item non-responses (NR), 'don't know' (DK) and inconsistent answers (IC) included in all specifications. Robust standard errors are reported in parentheses, and statistical significance at the 10, 5, and 1 percent levels is indicated by *, **, and ***, respectively. Source: Author computations using data from merged TNS2014 and TNS2015 surveys in France.

TABLE 3: Stockholdings

VARIABLES	(1) $Pr(stocks > 0)$	(2) $Pr(stocks > 0)$	(3) $Pr(stocks > 0)$ *placebo test*	(4) $Pr(stocks > 0)$ *placebo test*	(5) $E(\%FW > 0)$	(6) $E(\%FW > 0)$
$\%FC\ Inform.$	0.00263***		-0.00105		0.0293	
	(0.000600)		(0.000781)		(0.0216)	
$\%OC\ Inform.$	0.000111		0.000966		0.0291	
	(0.00126)		(0.00136)		(0.0408)	
$\%FC\ Particip.$		0.00210***		0.000115		0.0308
		(0.000660)		(0.000756)		(0.0233)
$\%OC\ Particip.$		0.00240*		-0.00187		0.0657
		(0.00125)		(0.00141)		(0.0431)
$Expec.\ R$	0.204**	0.199**	0.195**	0.194**	10.55***	11.14***
	(0.0953)	(0.0934)	(0.100)	(0.100)	(3.670)	(3.909)
$Risk\ aversion$	-0.00409**	-0.00407**	-0.00385**	-0.00399**	-0.120**	-0.124*
	(0.00185)	(0.00180)	(0.00166)	(0.00165)	(0.0606)	(0.0642)
Controls	yes	yes	yes	yes	yes	yes
Observations	2,525	2,525	2,512	2,512	2,294	2,294
Log-likelihood	-1202	-1204	-1215	-1214	-3634	-3634
LR χ^2	435.0	420.1	398.6	396.2	375.9	375.7

Notes: Marginal effects from probits of stock market participation (columns 1-4) and tobits of share of financial wealth invested in the stock market (direct or indirect), conditional on investing (columns 5-6), on share of financial and outer circles informed about or participating in the stock market . In all cases we control for household characteristics (age, gender, marital status, number of children, education, region of residence, employment, income, savings). Dummies for item non-responses (NR), 'don't know' answers (DK) and inconsistent answers (IC) included in all specifications. Marginal effects are calculated excluding IC observations. Standard errors are reported in parentheses, and statistical significance at the 10, 5, and 1 percent levels is indicated by *, **, and ***, respectively. Source: Author computations using data from merged TNS2014 and TNS2015 surveys in France.

TABLE 4: Bivariate probits

VARIABLES	(1) $Pr(stocks > 0)$	(2) $Pr(FC > 0)$	(3) $Pr(stocks > 0)$	(4) $Pr(FC > 0)$
$\%FC\ Inform.$	0.00255***			
	(0.000616)			
$\%OC\ Inform.$	0.000174			
	(0.00126)			
$\%SC\ Inform.$		0.00292**		0.00291**
		(0.00137)		(0.00136)
$\%FC\ Particip.$			0.00214***	
			(0.000675)	
$\%OC\ Particip.$			0.00230*	
			(0.00126)	
$\%SC\ Particip.$		-0.000461		-0.000470
		(0.00144)		(0.00143)
$Expec.R$	0.234*	0.0589	0.228*	0.0584
	(0.120)	(0.112)	(0.117)	(0.111)
$Risk\ Aversion$	-0.00400*	-0.00447*	-0.00402*	-0.00444*
	(0.00229)	(0.00243)	(0.00224)	(0.00241)
Controls	yes	yes	yes	yes
Observations	1,684	1,684	1,684	1,684
Log-likelihood	-1817	-1817	-1817	-1817
LR χ^2	596.3	596.3	589.5	589.5
$p-value$	0	0	0	0
ρ	0.0115	0.0115	0.0247	0.0247
Wald χ^2, $H_0 : \rho = 0$	0.0504	0.0504	0.240	0.240
$p-value$	0.822	0.822	0.624	0.624

Notes: Marginal effects from bivariate probits of (i) stock market participation (columns 1 and 3) and (ii) formation of financial circle (columns 2 and 4). In all cases we control for household characteristics (age, gender, marital status, number of children, education, area, employment, income, savings). Dummies for item non-responses (NR), 'don't know' (DK) and inconsistent answers (IC) included in all specifications. Marginal effects are calculated excluding IC observations. Standard errors are reported in parentheses, and statistical significance at the 10, 5, and 1 percent levels is indicated by *, **, and ***, respectively. Source: Author computations using data from merged TNS2014 and TNS2015 surveys in France.

TABLE 5: Summary statistics

VARIABLES	Mean	St.Dev.	Min.	Max.	Observations
N in Social Circle	52.56	77.01	0	999	2,334
N in Financial Circle	3.160	6.746	0	100	2,243
% SC Particip.	10.61	15.70	0	90	839
% SC Informed	12.47	15.80	0	80	903
% FC Particip.	20.13	29.01	0	100	704
% FC Informed	21.95	28.69	0	100	772
Expec. R	0.0162	0.0894	-0.625	0.625	2,535
St. dev. Expec. R	0.0670	0.0708	0	0.387	2,535
D(StDev.ER=0)	0.343	0.475	0	1	2,743
Perc.. R	0.0361	0.120	-0.375	0.375	2,328
Stand. dev. Perc. R.	0.0665	0.0717	0	0.311	2,328
Risk aversion	34.90	11.76	0	40	3,670
Borrowing & Liq.Constr.	0.0292	0.168	0	1	3,670
Age<35	0.170	0.376	0	1	3,670
35<Age<50	0.244	0.429	0	1	3,670
50<Age<65	0.275	0.446	0	1	3,670
Age>65	0.311	0.463	0	1	3,670
Male	0.464	0.499	0	1	3,670
Married	0.602	0.490	0	1	3,670
Children at Home>0	0.241	0.428	0	1	3,670
College or more	0.376	0.484	0	1	3,670
reg1	0.168	0.374	0	1	3,670
reg2	0.0635	0.244	0	1	3,670
reg3	0.0817	0.274	0	1	3,670
reg4	0.0826	0.275	0	1	3,670
reg5	0.0959	0.295	0	1	3,670
reg6	0.142	0.349	0	1	3,670
reg7	0.115	0.319	0	1	3,670
reg8	0.123	0.328	0	1	3,670
reg9	0.128	0.334	0	1	3,670
Employed	0.518	0.500	0	1	3,670
Self-employed	0.0349	0.183	0	1	3,670
Retired	0.311	0.463	0	1	3,670
Assets<74999	0.232	0.422	0	1	3,670
75000<Assets<224999	0.536	0.886	0	2	3,670
224500<Assets<449999	0.703	1.271	0	3	3,670
450000<Assets	0.428	1.237	0	4	3,670
Income<11999	0.298	0.457	0	1	3,670
12000<Income<19999	0.547	0.891	0	2	3,670
20000<Income<29999	0.804	1.329	0	3	3,670
Income>30000	0.555	1.383	0	4	3,670
Saving=0	0.310	0.463	0	1	3,670
0<Saving<999	0.562	0.899	0	2	3,670
1000<Saving<4999	0.804	1.329	0	3	3,670
Saving>5000	0.397	1.196	0	4	3,670

Source: Authors' calculations on merged TNS 2014 & 2015 data set.