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, that provide insights regarding two channels via which social interactions may generally affect financial decisions. The first is a pure information effect, which arises solely from communicating and disseminating information to and from friends and acquaintances. The second is an imitation effect, broadly understood as comprising of social norm effects, complementarities, fads, etc. We find that both effects are positive, sizeable and significant. The more (and better) informed about the stock market members of respondents' social circles are, the higher the share of respondents' financial wealth that is invested in the stock market (information), in accordance with theoretical predictions. The same effect is found for more members of respondents' circles participating in the stock market (imitation). In the latter case however, we only find evidence of selective imitation, by identifying a positive and significant effect coming only from a subset of respondents' social circle with whom respondents interact regarding financial matters. These findings suggest that both directly and indirectly informative social interactions are important for financial behavior and stock market participation.

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

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

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'

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decisions to invest in the stock market. 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 communicating and disseminating information to and from friends and acquaintances and (ii) *imitation peer effects*, also referred to as *social utility motive*, broadly understood as comprising of social norm effects in preferences, complementarities, opinion transmission, etc.

The starting point of our analysis is a theoretical model of asset prices in a large information network, where agents are allowed to obtain information from peers, friends and acquaintances (information network) as well as from asset prices. The model is an extension of Ozsoylev and Walden (2011) to allow for heterogeneity in risk preferences as well as a more general information network structure. A key prediction of the model is that individuals with higher 'connectedness', i.e. with more and/or more informative social interactions, trade 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 thus the share of their wealth that is 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 beliefs and perceptions of stock market returns via probabilistic elicitation techniques. Our empirical analysis exploits cross-sectional variation for a representative sample by age and wealth of the population of France, collected in two stages, 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. Crucially, it also contains specific questions designed to obtain quantitative proxies of network characteristics that enable identification of information network effects on financial decisions from individual answers, in the spirit of the original 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; (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 their peers' behavior (and characteristics) instead of the actual behavior of their peers; (iii) as in Bursztyn et al. (2014), our main identification strategy for disentangling 'informed holdings' from 'uninformed holdings' of risky assets is to separately ask respondents' perceptions about the peers' holdings and peers' information, and (iv) the survey is done over a representative sample of a population of a developed, rich country (France), with a mature stock market and abundantly available information on financial markets.

Our empirical analysis suggests that an information effect indeed runs directly through from social interactions, first via expectations for stock market returns and second, and by a larger amount, to how much respondents invest in the stock market: a social circle that is perceived more informed about the stock market is associated with both higher expected returns about the stock market, and a higher share of respondents' financial wealth invested in stocks. However, the same is true for perceived participation in the stock market by respondents' social circles, indicating the presence of imitation as well.

There are various reasons why we have this finding: First, it could simply be that both effects (information and imitation) are present and strong. Second, it may be due to the fact that there is a high correlation between participation in the stock market and being informed the stock market. Third, these results (for both information and participation), may be due to unobserved correlated peer effects. To reinforce our evidence of an information channel and address this last issue, we put to use an interesting interpretation of the theoretical model in the design of the survey. 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. people that the individual interacts with regarding 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 people with whom they do not discuss financial matters).

With this novelty in place, we can address three issues in one go. First, and foremost, we can reinforce our main conclusion that there is a strong and significant pure information effect present: we find that when we regress the share of financial wealth invested in the stock market on two distinct variables, namely the proportions of one's financial and outer circles that are perceived to follow the stock market, 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 the respondents do not discuss financial matters with them, even though the outer circle may well be informed.

Second, it allows us to separate imitation into two types, and identify which one of the two is important for how much investors invest in the stock market. The first type is *mindless imitation*, i.e. a pure imitation effect, whereby respondents do what others in their circle do, due to e.g. peer pressure, or a fad effect. The second type is *selective imitation*, i.e. the imitation of behavior of others in one's circle that are considered knowledgeable and trustworthy about financial matters. In the case of selective imitation, investors are in some sense taking the actions of the knowledgeable members of their circles as informative signals, and although this cannot be thought of a pure information transmission effect, it does allow us to consider such social interactions as indirectly informative. We now find that when regressing the share of financial wealth invested in the stock market on two distinct variables proxying imitation, namely the proportions of one's financial and outer circles that are perceived to participate (invest) in the stock market, the effect of the former is again sizeable and significant, while the effect from the latter is statistically insignificant. This suggests that selective imitation is present, but we find no evidence in support of blind copying by respondents of the behavior of the members of their social circles regarding stock market participation.

Last, 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, 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, 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.

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 from peers effects on the willingness to invest in a new financial product. Similar to our findings, 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 work by Barnerjee et al. (2013) who conclude that most of peer effects on the take-up rates of a newly introduced micro-finance program in rural India is due to an information channel. Empirical work by Ozsoylev et al. (2014) exploits instead stock market transactions data to identify an empirical investor network from the time proximity between individual transactions. The main difference with these papers is our focus on the general population, which allows us to understand the financial decisions of an average individual of a representative sample, but also the decision making of individuals with a variety of demographic characteristics. In contrast, these papers look into the decision making and information flows in specific subgroups, like those who own a brokerage account (Bursztyn et al., 2014), professionally trade at the Instanbul Stock Exchange (Ozsoylev et al., 2014), or who live in rural Indian villages (Barnerjee et al., 2013). While there is a lot to be learned from such experiments and environments, where the exact network of relations and information flows can be constructed or inferred, they unavoidably come with biases not present in a representative sample of the population containing a significant proportion that is inactive in financial markets of a rich, developed country such as France. The similarities and differences with these papers are further discussed in Section 4.3.

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 and the generalization of their theorem and explain how the derived asset demand function will be used as a guide for identifying information peer effects.

There are two assets, one risky (stock) and one riskless (bond). The payoff of the riskless asset is 1. The payoff of the risky asset follows a normal distribution $X \sim N(\bar{X}, \sigma^2)$ and its price is p. The supply of stocks is random and is given by $Z_n = nZ$, where $Z \sim N(\bar{Z}, \Delta^2)$ and $\bar{Z} > 0$. [1] 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

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

and thus

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

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 the 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.[2] From the perspective of agent i, when he pools all the

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

[2] 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

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.[3] 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 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).[4] 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

precision of i's signal. This is a more attractive assumption, but complicates unecessarily the mathematical expressions for the assumptions needed in deriving the optimal demand function, without altering the actual expression that we end up using for the econometric specification.

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

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

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

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 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 following: 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 excess return (in particular x_i).

The model therefore predicts that higher connectedness makes investors trade more aggressively. In other words, 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 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 is for the risky asset responds to his/her pooled signals, and thus the 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 optimal individual demand (9) require us to only know the average connectedness β and the individual connectedness of investors, k_i^*, and not the exact structure of the network. Therefore in designing the survey and generating proxies for these variables, a representative sample from a large population, for which we can identify measures for k_i^* is sufficient for the research questions we address.

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. 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 3,670 respondents, out of which we recovered a total of 2,587 responses, corresponding to a response rate of 70.5%.

The questions that are important for proxying variables for 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 $\%FW$ and will be used as a proxy for demand for risky asset; we also use the same question to generate variable $\Pr(Stock > 0)$ which takes value 1 if respondents have given 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 perceptions about a future 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. 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.[5] 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 return on a buy-and-hold portfolio that tracks the evolution of the stock market index over a three-year time window). These questions are designed with the following four goals in mind.

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

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.[6] 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., 2015). Fourth, probabilistic elicitation of the most recent stock market return realization (over a three-year time window) 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.[7] Without it, households who do not invest because they expect 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 returns $\mathbb{E}\left(X|\mathcal{I}_i\right)$ and perceived 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 respondents. A main novelty of the survey is to distinguish between a broad circle of social acquaintances of respondents (*social circle*) and a smaller circle, which is a subset of the social circle, defined as the respondents' acquaintances with whom the respondents convene about financial matters (*financial circle*) 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 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.

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

[7] As an example of the former, Armantier et al. (2014) document substantial differences across households regarding the 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 on a sample of New Zealand firms.

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.

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 side-steps the reflection problem identified by Manski (1993).[8] 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.[9] The cross-sectional average point estimates for the perceived percentage of the social and financial circle that invests

[8] The reflection problem refers to the impossibility of separately identifying the effect of peers' *choices* (endogenous factors) on individual outcomes, when individual and peers' choices are made simultaneously and as a function of common contextual factors (i.e. group characteristics). If instead of considering peers' actual choices, one exploits the variation in individual perceptions about peers' choices, when combined with individual perceptions about peers' characteristics, identification can be achieved. Li and Lee (2009) actually find that subjective perceptions about peers' behaviour 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) for additional details.

[9] 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.

Abbreviation	Stands for	Questions	From
SC	Social circle	C1	TNS2015
FC	Financial circle	D1	TNS2015
OC	Outer circle	C1, D1	TNS2015
$\%SC\ Inform.$	Perceived members of FC informed about stock market	C7ii	TNS2015
$\%SC\ Particip.$	Perceived members of the SC investing the stock market	C7i	TNS2015
$\%FC\ Inform.$	Perceived members of FC informed about stock market	D16ii	TNS2015
$\%FC\ Particip.$	Perceived members of FC investing in stock market	D16i	TNS2015
$\%OC\ Inform.$	Perceived members of OC informed about stock market	C1, D1, C7ii/D16ii	TNS2015
$\%OC\ Particip.$	Perceived members of OC investing in stock market	C1, D1, C7i/D16i	TNS2015
$\%FW$	Share of financial wealth invested in stocks	C19	TNS2014
$Pr(Stock > 0)$	Positive fin. wealth invested in stock market	C19	TNS2014
$Perc.\ R$	Mean perceived past returns for the stock market	C42	TNS2014
$Expec.\ R$	Mean expected future returns for the stock market	C39	TNS2014

Table 1: Abbreviations and Notation.

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 calculated via

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

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

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 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.

4. Empirical results

In the empirical analysis that follows, we proxy the connectedness of respondents k_i^* with variables $\%SC\ Inform.$, $\%FC\ Inform.$, $\%OC\ Inform.$, as defined in the previous section. We focus on these variables, because simply the number of friends and acquaintances of an individual (in any of the three circles) is not enough to distinguish between those friends who are informed from those who are uninformed about the stock market. Questions C7ii/D16ii, from which we get these three variables, isolate explicitly the part of one's social and financial circles that may provide respondents with *information* regarding the stock market.

Although the model makes predictions only in the context of an information network, our data

VARIABLES	(1) Expec R	(2) Expec R	(3) Expec R	(4) Expec R	(5) Expec R
% SC Inform.		0.000307			
		(0.000202)			
% FC Inform.			0.000301**		
			(0.000118)		
% OC Inform.			-4.32e-05		
			(0.000191)		
% SC Particip.				0.000394	
				(0.000264)	
% FC Particip.					0.000299***
					(0.000115)
% OC Particip.					-2.16e-05
					(0.000254)
RA	-0.000731*	-0.000708*	-0.000674*	-0.000702*	-0.000684*
	(0.000382)	(0.000382)	(0.000385)	(0.000383)	(0.000385)
Controls			*See Appendix C for full table and details on controls*		
Constant	0.0464***	0.0405**	0.0429**	0.0418**	0.0437**
	(0.0166)	(0.0170)	(0.0173)	(0.0170)	(0.0170)
F	2.985	2.805	3.075	2.792	3.106
R^2	0.032	0.034	0.037	0.034	0.037
Observations	2,535	2,535	2,535	2,535	2,535

Standard errors in parentheses, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.
Source: authors' calculations on merged TNS 2014 & 2015 dataset.

Table 2: Specification (12). Least squares estimates of covariates on expected future stock market returns.

allows us to also explore how the participation of peers in the stock market affects one's demand for stocks. Broadly, questions C7i/D16i will be used to address whether '*what others do*' matters for an individual's decision to invest in the stock market. This follows regression analysis of canonical peer-effects models of social and economic interactions, where the demand of an agent for investing in the stock market is related to a weighted average of his perceived demands of his friends and acquaintances that also participate in the stock market.

The split of the whole social circle between financial and outer circle serves two purposes: First, as will become clear when we present the empirical results, it provides evidence against the presence of unobserved heterogeneity in our regressions. More interestingly, it helps us disentangle the imitation effect into mindless and selective, when we ask, is it '*what others do*' or '*what others that know do*' that matters for investing in the stock market?

4.1. Expectations.

We start by examining the presence of the first (indirect) effect of informative social interactions on demand for investing in the stock market, via expected returns.[10] A linearization of expression

[10]Standard models of financial choice under uncertainty predict that decisions should be based on expectations of aggregate market outcomes, and not on publicly available information about recent market outcomes since the

VARIABLES	(1) Expec R	(2) Expec R	(3) Expec R	(4) Expec R	(5) Expec R
% SC Inform.		3.23e-05			
		(0.000207)			
% FC Inform.			0.000216*		
			(0.000121)		
% OC Inform.			-0.000177		
			(0.000188)		
% SC Particip.				8.70e-05	
				(0.000286)	
% FC Particip.					0.000239**
					(0.000120)
% OC Particip.					-0.000251
					(0.000260)
Perc R	0.284***	0.283***	0.282***	0.283***	0.282***
	(0.0267)	(0.0266)	(0.0267)	(0.0266)	(0.0267)
RA	-0.000557	-0.000551	-0.000534	-0.000548	-0.000540
	(0.000385)	(0.000385)	(0.000386)	(0.000385)	(0.000386)
Controls		*See Appendix C for full table and details on controls*			
Constant	0.0297*	0.0272	0.0273	0.0275	0.0283*
	(0.0168)	(0.0171)	(0.0175)	(0.0170)	(0.0171)
F	6.431	5.905	5.882	5.907	5.915
R^2	0.170	0.171	0.173	0.171	0.173
Observations	2,173	2,173	2,173	2,173	2,173

Standard errors in parentheses, *** p < 0.01, ** p < 0.05, * p < 0.1.
Source: authors' calculations on merged TNS 2014 & 2015 dataset.

Table 3: Specification (12). Least squares estimates of covariates on expected future stock market returns, including perceived returns.

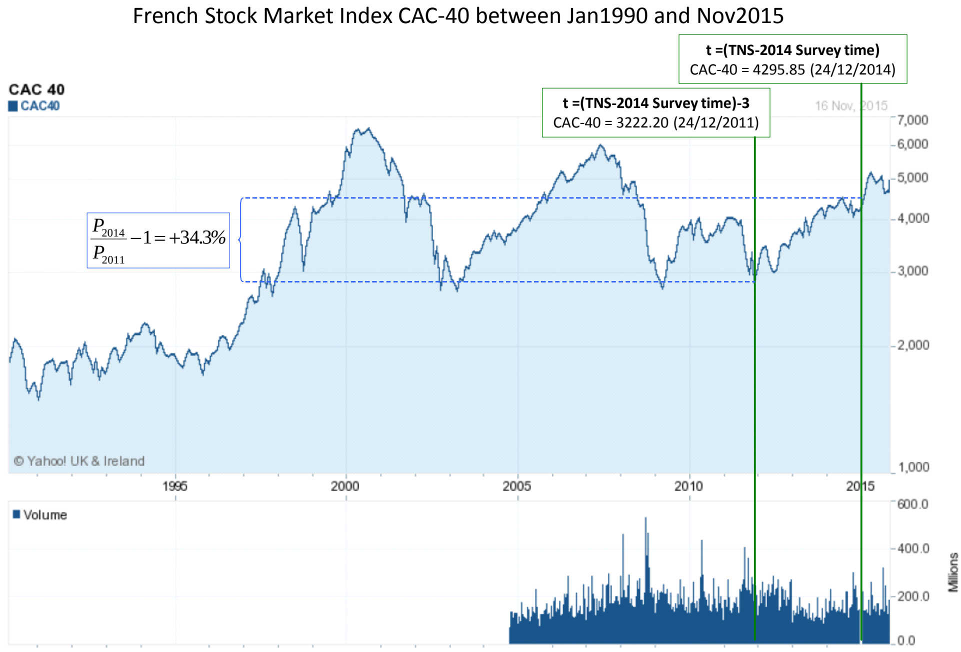

Figure 1: The French Stock Market Index CAC-40 between January 1990 and November 2015. Between December 2011 and December 2014 (3 years prior to the time of the survey) the index had increased by around 34%. Source: Authors' calculations from Yahoo Finance monthly data, available online.

(8) suggests a specification

$$Expec.\ R = \kappa_0 + \kappa_1 k_i^* + \kappa_2 D_i^e + \kappa_3 Perc.\ R + \kappa_4 \rho_i + \kappa \boldsymbol{\tau}_i + w_i \tag{12}$$

where w_i is an individual zero-mean error term distributed normally conditional on covariates and $\boldsymbol{\tau}_i$ is a vector individual characteristics. The controls included in vector $\boldsymbol{\tau}_i$ for all specifications are age, gender, marital status, number of children, education, geographical region, employment status, assets, income, borrowing, liquid savings. In all the specifications we also include non-response dummies in order to control for item non-responses.[11] A detailed list and explanations are provided in Appendix B.

Figure 1 shows historical monthly data of the French stock market index CAC-40, from January 1990 to November 2015. The index dropped by nearly 25% at the time of the sovereign-debt crisis

latter should be incorporated into respondents' expectations, since they are conditioned upon it (Brandt, 2010). However, a recent strand of the literature finds that subjective expectations do actually explain financial decisions (e.g. Dominitz and Manski, 2007; Kezdi and Willis, 2009; Hurd et al., 2011).

[11] Controlling for item non-response to the expectations and perceptions questions is important because we are identifying an information effect (from acquaintances with whom the respondent exchanges on financial matters). The fact that controlling for item non response to those questions leaves the size and statistical significance of the main effect unchanged (of others' information on own financial decision) provides additional evidence of the robustness of the identified channel, i.e. those who are unable/unwilling to respond are are as likely not to invest as they are likely not to exchange on financial matters with friends and acquaintances. The same approached has been used by Dimmock, et. al. (2016).

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 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 one. Given the substantial turmoil experienced by the stock market index over the recent period, it is likely that respondents are particularly aware of the recent stock market evolution, but provide very heterogeneous and uncertain answers regarding its future evolution.

The actual stock market returns over the three-year period in question were actually equal to +34.3%. The average cross-sectional perception of respondents is equal to +3.6%, therefore, upwards deviations from the cross-sectional mean and positive associations with perceived returns are interpreted as consistent with respondents being well informed about the stock market. Moreover, the average cross-sectional subjective expectation of respondents is equal to +1.6%, which is substantially lower than the expected returns that could be computed by December 2014 from simple extrapolation of publicly available time series data. Again, upwards deviations from the cross-sectional mean and positive associations with subjective expected returns are interpreted as consistent with respondents' expectations being more in line with available statistical evidence.

Tables 2 and 3 reports results from regressing expected returns on the different measures of connectedness and participation of peers, without and with perceived returns respectively as additional controls. The specification for columns (2) and (3) includes only the information variables, k_i^*, and columns (4) and (5) only the imitation variables D_i^e. Columns (2) and (4) from both tables suggest that whether the members of the respondents' social circles are informed about or invest in the stock market does matter for forming their subjective expectations on stock market returns. Once however the broad social circle is split into the two subgroups of financial and outer circle, we see evidence of the pure information and selective imitation channels on the formation of expectations. In columns (3) and (5) of both tables, the share of financial circle informed and the share of financial circle investing in the stock market is small, but nevertheless positive and significant. This confirms the model prediction that is, in a world of pessimistic perceptions of stock market returns, having *informative* social interactions (financial circle) corrects respondents' expectations of returns upwards towards the true return, whether via a pure information channel or via selective imitation. Table 3 suggests that a large effect on subjective return expectations comes from perceived returns, but even when controlling for perceived returns, the main result survives.

In summary, to the extend that expectations of returns are important for how much investors invest in the stock market, we find that informative social interactions play a positive (albeit small) role in determining expected returns of respondents.

4.2. Pure information and selective imitation.

Next, we turn to examining the importance of informative social interactions for directly determining demand for investing in the stock market, as suggested by expression (9). Reorganizing this indicates that the risk adjusted individual demands depend on a term that is common to all

VARIABLES	(1) Pr(Stock > 0)	(2) Pr(Stock > 0)	(3) Pr(Stock > 0)	(4) Pr(Stock > 0)	(5) Pr(Stock > 0)
% SC Inform.		0.00943***			
		(0.00313)			
% FC Inform.			0.00844***		
			(0.00177)		
% OC Inform.			0.00126		
			(0.00317)		
% SC Particip.				0.0170***	
				(0.00326)	
% FC Particip.					0.00783***
					(0.00195)
% OC Particip.					0.00684**
					(0.00333)
Expec R	0.814**	0.770**	0.680**	0.733**	0.678**
	(0.323)	(0.321)	(0.320)	(0.323)	(0.320)
RA	-0.0147**	-0.0140**	-0.0137**	-0.0139**	-0.0140**
	(0.00628)	(0.00626)	(0.00624)	(0.00621)	(0.00622)
Controls			*See Appendix C for full table and details on controls*		
Constant	-1.056***	-1.107***	-1.119***	-1.170***	-1.153***
	(0.288)	(0.296)	(0.302)	(0.295)	(0.300)
Log-likelihood	-1223	-1214	-1202	-1206	-1203
LR χ^2 (p-value)	396.1	401.7	435.4	419.0	422.7
Pseudo R^2	0.154	0.160	0.168	0.166	0.168
Observations	2,525	2,525	2,525	2,525	2,525

Robust standard errors in parentheses, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.
Source: authors' calculations on merged TNS 2014 & 2015 dataset.

Table 4: Specifications (13) and (14). Probit conditional marginal effects of covariates on the share of all financial wealth invested in the stock market.

VARIABLES	(1) % FW	(2) % FW	(3) % FW	(4) FW	(5) % FW
% SC Inform.		0.234**			
		(0.0973)			
% FC Inform.			0.142**		
			(0.0575)		
% OC Inform.			0.00784		
			(0.100)		
% SC Particip.				0.277***	
				(0.0977)	
% FC Particip.					0.150**
					(0.0599)
% OC Particip.					0.147
					(0.105)
Expec R	36.33***	35.20***	33.40***	34.49***	32.94***
	(11.56)	(11.54)	(11.52)	(11.53)	(11.53)
RA	-0.374*	-0.366*	-0.380**	-0.365*	-0.371*
	(0.192)	(0.192)	(0.191)	(0.192)	(0.191)
Controls		*See Appendix C for full table and details on controls*			
Constant	-37.00***	-37.53***	-35.36***	-36.88***	-36.72***
	(9.089)	(9.264)	(9.331)	(9.249)	(9.311)
Log-likelihood	-3643	-3637	-3634	-3635	-3632
LR χ^2 (p-value)	358.0	370.3	376.3	373.9	379.5
Pseudo R^2	0.0468	0.0484	0.0492	0.0489	0.0497
Observations	2,294	2,294	2,294	2,294	2,294

Standard errors in parentheses, *** p $<$ 0.01, ** p $<$ 0.05, * p $<$ 0.1.
Source: authors' calculations on merged TNS 2014 & 2015 dataset.

Table 5: Specifications (13) and (14). Tobit conditional marginal effects of covariates on the share of all financial wealth invested in the stock market.

agents, and a term that is individual-specific. Since we are exploiting the variation across agents, a linearization of (9) suggests the following Tobit econometric specification for agent i's share of financial wealth invested in the stock market:

$$D_i = \%FW = \max\{0,\ \lambda_0 + \underset{(+)}{\lambda_1} k_i^* + \underset{(+)}{\lambda_2} (x_i - p) + \lambda_3 Expec_i\ R + \underset{(-)}{\lambda_4} \rho_i + \boldsymbol{\lambda}\boldsymbol{\tau}_i + u_i\}, \tag{13}$$

where u_i is an individual-specific unbiased error term that the individual observes, but the econometrician does not. The zero term within it captures the observed prevalence of non stockholders in the general population. The vector $\boldsymbol{\tau}_i$ contains individual characteristics for respondent i.[12] The signs under the constant coefficients indicate the theoretically predicted signs: more/stronger connections (λ_1), a higher excess return (λ_2) and lower risk aversion (λ_3) increase the fraction of financial wealth invested in the stock market, controlling for individual characteristics. The main novel empirical prediction we seek support for from the survey data, within a rational model of financial risk taking, is the presence of an information effect from social interactions, i.e. a positive and significant estimate for λ_1.

In regression analysis of canonical peer-effects models of social and economic interactions, the demand of an agent for investing in the stock market is related to a weighted average of his perceived demands of his friends and acquaintances that also participate in the stock market. Therefore and in order to examine the role of selective imitation, we also consider the following specification

$$D_i = \%FW = \max\{0,\ \lambda_0 + \lambda_1 D_i^e + \underset{(+)}{\lambda_2} (x_i - p) + \lambda_3 Expec_i\ R + \underset{(-)}{\lambda_4} \rho_i + \lambda \boldsymbol{\tau}_i + u_i\}. \tag{14}$$

An imitation effect, broadly understood, is present if the parameter λ_4 is strictly positive and statistically significant, when D_i^e is taken to be the respondent's social circle. We call the effect 'selective imitation', if when splitting the social circle into financial and outer, the coefficient is significant for members of the financial circle. Our main results are presented in tables 4 and 5.

Table 4 reports results from estimating a probit econometric specifications of the extensive margin only, that are otherwise similar to specifications (13) and (14). Columns (2) and (3) provide evidence of a very significant information effect: the probability of investing in the stock market is associated with higher share of informed members of the social circle, and when the social circle is split between financial and outer circle, it is the share of the financial circle that follows the stock market that matters for the investment decision. The coefficient for $\%OC\ inform.$ is insignificant because although some members of one's outer circle may follow the stock market, by definition of the survey questions, the respondent does not discuss with these members any financial matters, thus any information they hold is irrelevant for the stock market participation decision of the respondent. Columns (4) and (5) provide similar evidence for the importance of peers' participation in the stock market for the probability of investing in the stock market. Looking at the social circle alone, a strong significant effect is present (double in size from the information effect in column (4)), indicating possible imitation. When the social circle is split into

[12] The vector $\boldsymbol{\tau}_i$ containst the following controls: age, gender, marital status, number of children, geographical region, employment status, assets, income, borrowing, liquid savings. The detailed definitions of these can be found in Appendix B.

financial and outer circles however, the participation of the members of the financial circle is more important than that of the members of outer circle (the coefficient for the latter is smaller and less significant), supporting the view that respondents selectively imitate their peers '*that know*'. We also note that there is a substantial effect on the probability of investing in the stock market from the expectations of future returns, but this becomes smaller when we include $\%FC\ inform$ and $\%OC\ inform$, or $\%FC$ *particip* and $\%OC$ *particip* in the regressors.

Last, we turn to the estimates from the Tobit specification that quantify the effects we wish to isolate. The results from Table 5 confirm the findings from Table 4 and provide evidence of a sizeable direct information effect. Once again, when the circle of acquaintances is split between financial and outer circles, the information effect is only significant for the financial circle. When the average proportion of an individual's financial circle that is perceived to follow the stock market increases by one percentage point, the share of wealth that the individual invests in the stock market increases by 0.142 pp among stockholders, and by 0.0310 pp overall.[13]

To get a sense of what the actual size of this information effect is on the share of financial wealth invested in the stock market of a typical stockholder, we do the following simple numerical experiment: A typical stockholder in our sample has total financial wealth (excluding housing) that is €96,395.[14] We find that respondents that are stockholders invest on average about 21.4% of their financial wealth in the stock market, i.e. the typical stockholder invests about €20,628 in the stock market. We next impute how much more the average stockholder invests when his financial circle has an additional member that is informed about the stock market. The average number of people in the financial circle of stock holders is 3, and on average, respondents that are stock holders report that 28% of their financial circle is informed about the stock market. This translates approximately to one in three people from the financial circle is informed, so that the marginal effect of having one additional informed person in the financial circle (i.e. two out three people, or 66% of the financial circle) from Table 5 is about $0.142 \times (66 - 28.1) = 5.4$ pp. In other words, the stockholder now invests 26.8% of his financial wealth to the stock market instead of 21.4%, which translates to an additional €5,205 invested in the stock market for an additional acquaintance in the respondent's financial circle that is perceived informed about the stock market. This translates to 5.4% increase of financial wealth invested in the stock market.

Columns (4) and (5) of Table 4 support the existence of a selective imitation effect, as seen with the previous specifications. When the average proportion of an individual's financial circle that is perceived to invest in the stock market increases by one percentage point, the share of wealth

[13]The uncoditional average marginal effect is obtained from estimating a separate probit specification for the probability of being a stockholder (directly or indirectly) conditional on the same covariates, and employing the standard decomposition:

$$\begin{aligned}\frac{\partial E(D_i|\boldsymbol{\tau}_i)}{\partial(\%\ FC\ Inform.)} &= P(D_i > 0|\boldsymbol{\tau}_i) \times \frac{\partial E(D_i|\boldsymbol{\tau}_i, D_i > 0)}{\partial(\%\ FC\ Inform.)} \\ &= 0.2179 \times 0.142 = 0.0310\end{aligned}$$

[14]Respondents have reported their total financial wealh (excluding housing), in question C16 (TNS2014), with bracketed entries. The average financial wealth reported is calculated after setting 0 as the minimum and €1m as the maximum, and using the mid point from each bracket.

that the individual invests in the stock market increases by 0.150 pp among stockholders, and by 0.0327 pp overall.[15]

4.3. Discussion. Barnerjee et al. (2013) and Bursztyn et al. (2014) separately identify the relative importance of both information and imitation effects for individual financial behavior pursuing different strategies in different experimental settings. Barnerjee et al. (2013) replace the unconditional individual probability of participation in a novel microfinance programme by the (structurally estimated) individual probability of participation, conditional on individual information sourced from friends. Once informed, they find that an agent's decision to participate in the programme is not significantly influenced by the fraction of her friends participating, concluding that it is mainly an information effect.[16] This may seem to be in contrast to our findings, but it is not. This is because in their setting social links function simply as vehicles for transmitting otherwise inaccessible information, that makes agents *aware* about a financial product. In our framework, agents are already aware of the financial opportunities but potentially pool different pieces of private information signals from a variety of acquaintances, in order to refine their perceptions of potential returns on their stock market investments.

Bursztyn et al. (2014) instead 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 through the social peer who was intending to buy but was nevertheless unable to (also randomly). To disentangle the two effects, they put investors in pairs according to whether a social tie exists between them, and randomly assign the opportunity to purchase the new financial product to one of them. The authors then sequentially allocate randomly (1) the actual purchase of the asset amongst those who were offered the opportunity and expressed an interest in buying it, and (2) the information that the socially related investor had actually managed to purchase the asset. The authors are then able to separately identify a social utility component from a social learning component in financial decision making by (i) comparing the effect on the propensity to invest of the socially paired investor who was not initially given the opportunity to invest, of providing him information (1) relative to no information (identifies *social learning*), and (ii) examining the differential effect on the propensity to invest of the socially paired investor of information (2) versus information (1) (the difference identifies the *social utility* component). The overall peer effect on the propensity to invest obtains from the differential impact of information (2) relative to no information.

[15] The uncoditional average marginal effect is obtained from estimating the probit specification for the probability of being a stockholder (directly or indirectly) conditional on the same covariates, and employing the standard decomposition:

$$\begin{aligned}\frac{\partial E(D_i|\boldsymbol{\tau}_i)}{\partial(\%\ FC\ Particip.)} &= P(D_i>0|\boldsymbol{\tau}_i)\times\frac{\partial E(D_i|\boldsymbol{\tau}_i, D_i>0)}{\partial(\%\ FC\ Particip.)}\\ &= 0.2179\times 0.150 = 0.0327\end{aligned}$$

[16] In their work, both the identification of the actual network structure and control over the information spreading through it exploiting temporal and geographical variation in injection points are instrumental.

Here, we carry out a different analysis in an attempt to address similar questions. The main difference between these two papers and our approach is that while both papers work with a newly introduced financial product, we consider the decision to invest in the stock market, a pre-existing, old financial opportunity which is publicly available to all. This is done in the context of rich developed country (France) with a healthy and well functioning stock market. Relative to Barnerjee et al. (2013) or Bursztyn et al. (2014), we replace actual financial behavior and characteristics of peers with individual perceptions of friends and acquaintances' decisions, and strength of social links, k_i^*. That effectively captures both 'contextual' and 'endogenous' peer effects in decisions, without having to resort to a reduced form econometric specification obtained from an equilibrium model of behavior relying on (strong) consistency conditions for expectations (Blume et al., 2011).

Our empirical results throughout the paper suggest that the more informed an agent's financial circle is about the stock market, the more he/she tends to invest in the stock market, and similarly for perceived participation of peers. We interpret this finding to be in accordance with the predictions of the model, i.e. conditional on investing, an agent collects more information from better informed peers, and thus trades more aggressively. However, the estimates from columns (2) and (4) from all tables are also consistent with an unobserved heterogeneity explanation, which in our context we can think of as homophily: Agents tend to socialize or discuss financial matters with others that are similar to them and therefore they tend to have similar attitudes towards investing in the stock market. We use a battery of approaches to tackle this problem. First, the split between financial and outer circle, and the fact there are no significant estimated effects from the outer circle that affect the demand for stock market investment suggests that it is not similarities among members of the social circles that drive the results. Second, we use four questions (C5, D6, D7 and D8) from the TNS2015 questionnaire that asks 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 does not indicate strong homophily, thus lending more support to our model backed interpretation of the estimated effects. Third, we run placebo tests on the financial circles of respondents [TBC]. All these suggest that our results are not biased and that they indeed capture the fact that informative social interactions, whether directly or indirectly, are associated with more investment in the stock market by individuals.

5. Summary

We provide a theoretical foundation for a pure information peer effect of social interactions on individual demands for risky assets and find strong empirical support for it by exploiting purpose-made (by us) novel survey data for a representative sample of the French population by age, wealth and asset classes, collected in December 2014 and May 2015. When estimating a canonical peer effects regression model to disentangle imitation from information peer effects on stock holdings and the share of financial wealth invested in the stock market, we find that both are present and are quantitatively important, in line with the results obtained by Bursztyn et al. (2014), and therefore extending them to the general population. When inquiring into the actual mechanism by which respondents' source information from peers, we found that respondents' subjective expectations of stock market returns are determined by both imitation and information effects from peers. By separating the social circle of respondents into two complementary circles, the financial circle (i.e. people that respondents discuss their financial matters) and the outer circle (everyone else), we are able to conclude that our results are not consistent with mindless imitation of stock market participation. If there is in any imitation of others' financial behavior, it is selective and comes from social interactions that are informative.

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APPENDICES INCOMPLETE - TBC

A. Noisy Rational Expectations Equilibrium

We conjecture that the risky asset price has the form

$$p = \pi_0 + \sum_{j=1}^{n} \pi_j x_j - \gamma Z_n. \tag{15}$$

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.

$$\lim_{n\to\infty} \frac{\|W\|_\infty}{n} = 0 \tag{16}$$

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

B.1. Expec R and Perc R: Subjective Expectations and 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 questions (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 $t+5$, $R_{t+1}(5) \equiv \frac{P_{t+5}}{P_t} - 1$.[17] 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:

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

and zero elsewhere, i.e. $R_{t+1} \in (-\infty, -R^i_{\min}) \cup (R^i_{\max}, +\infty)$. Table 6 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 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):

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[17] 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%

Question C42 inquires household i about the subjective relative likelihood of occurrence, $p_{t,k}^{i}$, 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 in 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 inquiring about beliefs instead, and which is described below. Accordingly, households' subjective likelihoods are given by:

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

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 December 2011 (CAC 40 = 3222.2) and December 2014 (CAC 40 = 4295.85), the index had increased an overall 34.3%. Figure 1 shows the information time window chosen within the wanderings of the CAC-40 index between 1990 and 2015. Table 6 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 recent three-year cumulative stock market return (Dec. 2011-Dec. 2014). Although this might be due to imperfect recall given the unusually long horizon (although respondents were given enough time to access the internet or else, and report the correct response) 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. Although the big spread around the most recent three-year cumulative stock market perceived return came as no surprise (possibly indicating ambiguity), it is remarkable that it remains smaller than the spread around the expected five-year ahead cumulative stock market return.

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

Table 6: Questions C39 and C42, TNS 2014. Summary Statistics.

Figures 1a and 1b below report the histograms of respondents' answers to the subjective expectations and perceptions questions, respectively, for both the mean (left panel) and the standard deviation of mean responses (right panel). Figure 1a (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 mis-perception 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.

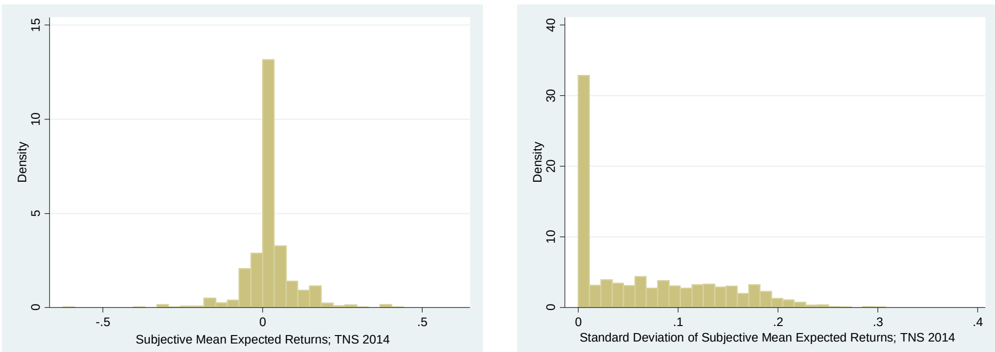

Figure 1a: Histograms of the subjective mean (left panel) expected five-year ahead cumulative return, and its standard deviation (right panel); TNS2014.

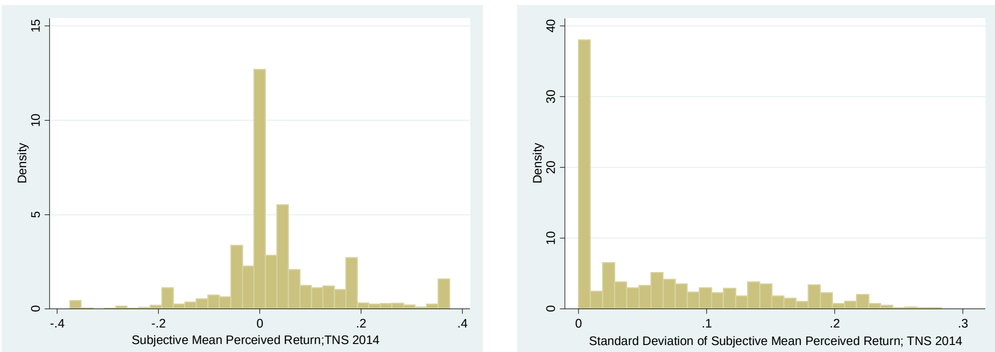

Figure 1b: Histograms of the subjective mean (left panel) perceived three-year cumulative realized return, and its standard deviation (right panel); TNS2014.

Arrondel et al. (2011) report that categorical answers to frequency, variety and access specialised media, advice from professionals, as well as the number of stock market transactions carried over the last year, increase the likelihood of being informed. Interestingly, parents' stock ownership status ('cultural transmission'), parents' educational attainment or family background do not increase the odds of being 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 bais 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) fidings 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).

B.2. %FW: *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 ask respondents to report their total financial wealth (excluding housing) and their given brackets (see below for further details). The translated wording for question C19 is:

C19: Approximately what percentage of these total financial wealth have you invested in listed or unlisted shares, directly or in unit trusts, in a personal equity plan or not (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 7.

B.4. Demographics and other control Variables.

Endowments.

Total wealth: In the survey (question C29), the respondent is asked which of the ten predefined

VARIABLES	# obs.	Mean	St. D.	Min	Max
C1, # SC	2334	52.56	77.00	0	999
D1, # FC	2243	3.16	6.74	0	100
C7i	839	10.61	15.70	0	90
C7ii	903	12.46	15.79	0	80
D16i	704	20.13	29.00	0	100
D16ii	772	21.94	28.68	0	100

Table 7: Questions C1, C7, D1 and D16, TNS 2015. Summary Statistics.

available brackets corresponds to the household's non-human wealth, including housing, estates and professional assets (without excluding debt).[18] Total wealth is given in Euros.

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.[19] 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. Income refers to the respondent's annual income (earnings, pensions, bonuses, etc.) in Euros, net of social contributions but before personal income taxes.[20] In addition, TNS reports also the net gross monthly income of the household, in Euros.

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

[18] 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 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.

[19] 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 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.

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

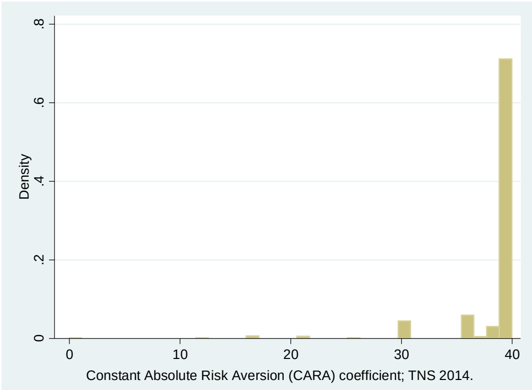

Figure 2: Histogram of responses to the hypothetical lottery that enables elicitation of the respondent's coefficient of absolute risk aversion (CARA) -TNS 2014 survey question C44.

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 (CARA): 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 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 (CARA) 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. 2 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 (CARA) 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.

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 30% of respondents ticked the first entry.

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'.

Delegation/Inertia.

Self portfolio management: The survey asks the respondent who takes household's financial decisions (stocks, SICAV/FCP bonds, life insurance contracts, saving accounts). Respondents who answer 'themselves' or 'them with their partners' are coded as 1, and 0 otherwise (which includes sharing some decisions with a financial advisor, or the financial advisor taking all decisions on the households' behalf).

Frequency of recent trades: Respondents are asked about the number of stock market operations closed over the year prior to the date in which the survey was conducted (Dec 2013-Dec 2014). The answers are categorical: no operations, 1-2 operations, 3-5 operations, 6 or more operations.

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).

Sources of Information variables:

* Respondents are inquired, for each alternative source of information (Friends, family, financial advisors, general media and specialised media), about the relative frequency of consultation (often, sometimes or never). For each information source, a dummy variable is created which takes value 1 if the answer is 'often', and 0 otherwise.

* Respondents are inquired, for each alternative source of TV information (General information and economics emissions) , about the relative frequency of consultation (very often, often, occasionally, sometimes or never). For each information source, a dummy variable is created which takes value 1 if the answer is 'often' or 'very often', and 0 otherwise.

C. Full Tables

In all the tables, item non-response categorical variables are included, unless otherwise stated. The reference categories used are 'less than 35', 'highschool', 'reg 1', and first quartiles of total wealth, income and saving, wherever relevant.

VARIABLES	(1) Expec R	(2) Expec R	(3) Expec R	(4) Expec R	(5) Expec R
% SC Inform.		0.000307			
		(0.000202)			
% FC Inform.			0.000301**		
			(0.000118)		
% OC Inform.			-4.32e-05		
			(0.000191)		
% SC Particip.				0.000394	
				(0.000264)	
% FC Particip.					0.000299***
					(0.000115)
% OC Particip.					-2.16e-05
					(0.000254)
RA	-0.000731*	-0.000708*	-0.000674*	-0.000702*	-0.000684*
	(0.000382)	(0.000382)	(0.000385)	(0.000383)	(0.000385)
35<Age<50	-0.000213	0.000107	-0.000275	-0.000173	-0.000351
	(0.00584)	(0.00580)	(0.00582)	(0.00580)	(0.00580)
50<Age<65	0.000202	0.000551	0.000836	0.000621	0.000856
	(0.00621)	(0.00618)	(0.00617)	(0.00618)	(0.00618)
Age>65	0.00605	0.00644	0.00633	0.00672	0.00687
	(0.00865)	(0.00863)	(0.00870)	(0.00866)	(0.00872)
Male	0.0118***	0.0118***	0.0114***	0.0116***	0.0114***
	(0.00388)	(0.00388)	(0.00388)	(0.00388)	(0.00387)
Married	-0.00938**	-0.00953**	-0.00960**	-0.00934**	-0.00932**
	(0.00436)	(0.00436)	(0.00437)	(0.00436)	(0.00436)
Children at Home > 0	0.00415	0.00420	0.00461	0.00442	0.00447
	(0.00514)	(0.00514)	(0.00516)	(0.00513)	(0.00511)
College or more	0.00292	0.00241	0.00119	0.00226	0.00110
	(0.00407)	(0.00413)	(0.00414)	(0.00414)	(0.00415)
reg2	-0.00398	-0.00374	-0.00436	-0.00411	-0.00426
	(0.0100)	(0.0101)	(0.0100)	(0.0101)	(0.0100)
reg3	-0.00148	-0.00120	-0.00220	-0.00118	-0.00205
	(0.00750)	(0.00751)	(0.00749)	(0.00750)	(0.00750)
reg4	0.00755	0.00767	0.00710	0.00758	0.00699
	(0.00768)	(0.00769)	(0.00768)	(0.00769)	(0.00770)
reg5	0.000262	0.000652	0.000121	0.000335	0.000344
	(0.00749)	(0.00749)	(0.00744)	(0.00748)	(0.00746)
reg6	-0.00574	-0.00542	-0.00607	-0.00549	-0.00563
	(0.00623)	(0.00622)	(0.00620)	(0.00622)	(0.00622)
reg7	0.00989	0.0100	0.00895	0.00996	0.00932
	(0.00647)	(0.00650)	(0.00650)	(0.00647)	(0.00651)
reg8	-0.00286	-0.00274	-0.00320	-0.00287	-0.00328
	(0.00681)	(0.00680)	(0.00681)	(0.00681)	(0.00681)
reg9	0.00393	0.00414	0.00350	0.00414	0.00357
	(0.00691)	(0.00691)	(0.00692)	(0.00692)	(0.00693)
Employed	-0.0108	-0.0106	-0.0110	-0.0109	-0.0110
	(0.00694)	(0.00694)	(0.00696)	(0.00695)	(0.00696)
Self-employed	-0.0147*	-0.0142	-0.0147*	-0.0148*	-0.0145
	(0.00893)	(0.00897)	(0.00889)	(0.00898)	(0.00886)
Retired	-0.0154*	-0.0152*	-0.0148*	-0.0153*	-0.0152*
	(0.00854)	(0.00852)	(0.00858)	(0.00852)	(0.00858)

75000<Assets<224999	0.00249	0.00255	0.00216	0.00248	0.00225
	(0.00292)	(0.00291)	(0.00292)	(0.00292)	(0.00292)
224500<Assets<449999	0.000636	0.000599	0.000302	0.000519	0.000282
	(0.00199)	(0.00200)	(0.00199)	(0.00200)	(0.00199)
450000<Assets	0.00225	0.00210	0.00156	0.00184	0.00150
	(0.00179)	(0.00179)	(0.00179)	(0.00180)	(0.00180)
12000<Income<19999	-0.00231	-0.00231	-0.00232	-0.00221	-0.00243
	(0.00276)	(0.00276)	(0.00275)	(0.00275)	(0.00275)
20000<Income<29999	0.00136	0.00136	0.00118	0.00140	0.00124
	(0.00196)	(0.00195)	(0.00195)	(0.00194)	(0.00195)
Income>30000	0.00392**	0.00378**	0.00384**	0.00379**	0.00385**
	(0.00170)	(0.00169)	(0.00169)	(0.00168)	(0.00169)
Borrowing	-0.00857	-0.00828	-0.00786	-0.00812	-0.00816
	(0.0119)	(0.0120)	(0.0120)	(0.0120)	(0.0120)
NR(Assets)	-0.00635	-0.00626	-0.00663	-0.00641	-0.00659
	(0.00831)	(0.00833)	(0.00830)	(0.00834)	(0.00829)
NR(Income)	-0.0506	-0.0523	-0.0508	-0.0523	-0.0510
	(0.0420)	(0.0420)	(0.0417)	(0.0421)	(0.0417)
NR(RA)	-0.0632***	-0.0634***	-0.0620***	-0.0630***	-0.0625***
	(0.0238)	(0.0237)	(0.0238)	(0.0238)	(0.0238)
NR_sC72	-0.0346**	-0.0342*	-0.0330*	-0.0344**	-0.0326*
	(0.0175)	(0.0175)	(0.0172)	(0.0175)	(0.0174)
NR(% SC Particip.)				0.00712	
				(0.00515)	
NR(% SC Inform.)		0.00837			
		(0.00519)			
DK(% SC Particip.)				0.00169	
				(0.00497)	
DK(% SC Inform.)		0.00340			
		(0.00498)			
NR(% OC Inform)			-0.0384		
			(0.193)		
NR(% FC Inform)			0.00216		
			(0.00746)		
DK(% FC Inform.)			-0.00647		
			(0.00726)		
NR(% FC Particip.)					0.00139
					(0.00762)
DK(% FC Particip.)					-0.00709
					(0.00741)
NR(% OC Particip.)					-0.0167
					(0.256)
Constant	0.0464***	0.0405**	0.0429**	0.0418**	0.0437**
	(0.0166)	(0.0170)	(0.0173)	(0.0170)	(0.0170)
Log-likelihood					
F	2.985	2.805	3.075	2.792	3.106
R^2	0.032	0.034	0.037	0.034	0.037
Observations	2,535	2,535	2,535	2,535	2,535

Standard errors in parentheses, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Source: authors' calculations on merged TNS 2014 & 2015 dataset.

Table 8: Specification (12). Least squares estimates of covariates on expected future stock market returns, full table.

VARIABLES	(1) Expec R	(2) Expec R	(3) Expec R	(4) Expec R	(5) Expec R
% SC Inform.		3.23e-05			
		(0.000207)			
% FC Inform.			0.000216*		
			(0.000121)		
% OC Inform.			-0.000177		
			(0.000188)		
% SC Particip.				8.70e-05	
				(0.000286)	
% FC Particip.					0.000239**
					(0.000120)
% OC Particip.					-0.000251
					(0.000260)
Perc R	0.284***	0.283***	0.282***	0.283***	0.282***
	(0.0267)	(0.0266)	(0.0267)	(0.0266)	(0.0267)
RA	-0.000557	-0.000551	-0.000534	-0.000548	-0.000540
	(0.000385)	(0.000385)	(0.000386)	(0.000385)	(0.000386)
35<Age<50	0.000916	0.00122	0.000678	0.00121	0.00105
	(0.00577)	(0.00576)	(0.00577)	(0.00574)	(0.00572)
50<Age<65	0.00338	0.00367	0.00360	0.00378	0.00379
	(0.00623)	(0.00625)	(0.00623)	(0.00626)	(0.00622)
Age>65	0.00502	0.00547	0.00475	0.00561	0.00539
	(0.00894)	(0.00896)	(0.00900)	(0.00898)	(0.00898)
Male	0.00598	0.00615	0.00590	0.00609	0.00594
	(0.00390)	(0.00391)	(0.00391)	(0.00391)	(0.00391)
Married	-0.00741*	-0.00767*	-0.00788*	-0.00763*	-0.00767*
	(0.00426)	(0.00427)	(0.00428)	(0.00427)	(0.00427)
Children at Home > 0	0.00510	0.00505	0.00556	0.00517	0.00540
	(0.00517)	(0.00517)	(0.00519)	(0.00514)	(0.00514)
College or more	0.00243	0.00235	0.00149	0.00221	0.00134
	(0.00403)	(0.00410)	(0.00413)	(0.00411)	(0.00413)
reg2	-0.00111	-0.00119	-0.00157	-0.00118	-0.00122
	(0.0101)	(0.0102)	(0.0102)	(0.0102)	(0.0101)
reg3	-0.00710	-0.00726	-0.00796	-0.00723	-0.00791
	(0.00742)	(0.00741)	(0.00741)	(0.00742)	(0.00742)
reg4	0.00574	0.00548	0.00528	0.00549	0.00541
	(0.00790)	(0.00792)	(0.00790)	(0.00791)	(0.00793)
reg5	0.00202	0.00214	0.00180	0.00213	0.00215
	(0.00731)	(0.00732)	(0.00726)	(0.00731)	(0.00727)
reg6	-0.00784	-0.00786	-0.00830	-0.00784	-0.00796
	(0.00636)	(0.00638)	(0.00635)	(0.00638)	(0.00636)
reg7	0.00783	0.00772	0.00700	0.00770	0.00745
	(0.00633)	(0.00641)	(0.00641)	(0.00640)	(0.00642)
reg8	-0.00169	-0.00189	-0.00211	-0.00187	-0.00225
	(0.00677)	(0.00680)	(0.00680)	(0.00682)	(0.00681)
reg9	0.00111	0.00116	0.000623	0.00115	0.000710
	(0.00673)	(0.00675)	(0.00676)	(0.00675)	(0.00677)
Employed	-0.00705	-0.00707	-0.00715	-0.00715	-0.00714
	(0.00713)	(0.00714)	(0.00714)	(0.00713)	(0.00714)
Self-employed	-0.00264	-0.00253	-0.00282	-0.00266	-0.00259
	(0.00947)	(0.00950)	(0.00941)	(0.00947)	(0.00938)
Retired	-0.0100	-0.0101	-0.00938	-0.0101	-0.00971
	(0.00873)	(0.00874)	(0.00876)	(0.00873)	(0.00876)

75000<Assets<224999	0.00124	0.00131	0.000963	0.00127	0.00105
	(0.00279)	(0.00280)	(0.00279)	(0.00280)	(0.00280)
224500<Assets<449999	-0.00127	-0.00124	-0.00146	-0.00128	-0.00148
	(0.00197)	(0.00198)	(0.00198)	(0.00198)	(0.00198)
450000<Assets	-0.00126	-0.00125	-0.00168	-0.00134	-0.00170
	(0.00184)	(0.00184)	(0.00182)	(0.00184)	(0.00183)
12000<Income<19999	0.00175	0.00175	0.00178	0.00174	0.00163
	(0.00278)	(0.00278)	(0.00279)	(0.00278)	(0.00278)
20000<Income<29999	0.00297	0.00301	0.00290	0.00300	0.00286
	(0.00193)	(0.00193)	(0.00193)	(0.00193)	(0.00194)
Income>30000	0.00278	0.00281*	0.00283*	0.00278*	0.00280*
	(0.00169)	(0.00169)	(0.00169)	(0.00169)	(0.00170)
Borrowing	-0.0138	-0.0138	-0.0135	-0.0137	-0.0135
	(0.0126)	(0.0126)	(0.0127)	(0.0127)	(0.0127)
NR(Assets)	-0.00608	-0.00609	-0.00664	-0.00609	-0.00642
	(0.00864)	(0.00866)	(0.00864)	(0.00867)	(0.00862)
NR(Income)	-0.00622	-0.00753	-0.00701	-0.00775	-0.00715
	(0.0122)	(0.0120)	(0.0122)	(0.0122)	(0.0121)
NR(RA)	-0.0643**	-0.0654**	-0.0645**	-0.0653**	-0.0650**
	(0.0308)	(0.0306)	(0.0307)	(0.0307)	(0.0307)
NR_sC72	0.00232	0.00300	0.00336	0.00276	0.00332
	(0.0154)	(0.0155)	(0.0148)	(0.0155)	(0.0150)
NR(% SC Particip.)				0.00485	
				(0.00540)	
NR(% SC Inform.)		0.00486			
		(0.00517)			
DK(% SC Particip.)				0.000681	
				(0.00500)	
DK(% SC Inform.)		0.00147			
		(0.00480)			
NR(% OC Inform)			-0.173		
			(0.190)		
NR(% FC Inform)			0.00144		
			(0.00737)		
DK(% FC Inform.)			-0.00397		
			(0.00705)		
NR(% FC Particip.)					0.00275
					(0.00747)
DK(% FC Particip.)					-0.00259
					(0.00714)
NR(% OC Particip.)					-0.249
					(0.261)
Constant	0.0297*	0.0272	0.0273	0.0275	0.0283*
	(0.0168)	(0.0171)	(0.0175)	(0.0170)	(0.0171)
Log-likelihood					
F	6.431	5.905	5.882	5.907	5.915
R^2	0.170	0.171	0.173	0.171	0.173
Observations	2,173	2,173	2,173	2,173	2,173

Standard errors in parentheses, *** p < 0.01, ** p < 0.05, * p < 0.1.

Source: authors' calculations on merged TNS 2014 & 2015 dataset.

Table 9: Specification (12). Least squares estimates of covariates on expected future stock market returns, including perceived returns, full table.

VARIABLES	(1) Pr(St > 0)	(2) Pr(St > 0)	(3) Pr(St > 0)	(4) Pr(St> 0)	(5) Pr(St > 0)
% SC Inform.		0.00943***			
		(0.00313)			
% FC Inform.			0.00844***		
			(0.00177)		
% OC Inform.			0.00126		
			(0.00317)		
% SC Particip.				0.0170***	
				(0.00326)	
% FC Particip.					0.00783***
					(0.00195)
% OC Particip.					0.00684**
					(0.00333)
Expec R	0.814**	0.770**	0.680**	0.733**	0.678**
	(0.323)	(0.321)	(0.320)	(0.323)	(0.320)
RA	-0.0147**	-0.0140**	-0.0137**	-0.0139**	-0.0140**
	(0.00628)	(0.00626)	(0.00624)	(0.00621)	(0.00622)
35<Age<50	0.220**	0.232**	0.217**	0.216**	0.207**
	(0.103)	(0.104)	(0.105)	(0.105)	(0.105)
50<Age<65	0.209*	0.229**	0.230**	0.219**	0.223**
	(0.108)	(0.110)	(0.110)	(0.110)	(0.110)
Age>65	0.376**	0.391**	0.393**	0.395**	0.405**
	(0.160)	(0.161)	(0.160)	(0.161)	(0.161)
Male	0.141**	0.132**	0.122*	0.124**	0.122*
	(0.0622)	(0.0625)	(0.0631)	(0.0628)	(0.0629)
Married	-0.168**	-0.163**	-0.169**	-0.158**	-0.158**
	(0.0691)	(0.0695)	(0.0697)	(0.0696)	(0.0697)
Children at Home > 0	-0.209**	-0.207**	-0.203**	-0.204**	-0.205**
	(0.0894)	(0.0896)	(0.0905)	(0.0901)	(0.0904)
College or more	0.239***	0.214***	0.191***	0.211***	0.190***
	(0.0672)	(0.0675)	(0.0682)	(0.0678)	(0.0682)
reg2	-0.102	-0.0893	-0.106	-0.112	-0.109
	(0.144)	(0.145)	(0.146)	(0.147)	(0.146)
reg3	-0.0377	-0.0241	-0.0545	-0.0171	-0.0467
	(0.124)	(0.124)	(0.125)	(0.124)	(0.125)
reg4	0.0293	0.0412	0.0166	0.0361	0.00992
	(0.123)	(0.123)	(0.124)	(0.124)	(0.124)
reg5	-0.0202	-0.0150	-0.0286	-0.0246	-0.0259
	(0.123)	(0.124)	(0.124)	(0.124)	(0.124)
reg6	-0.0868	-0.0750	-0.0894	-0.0757	-0.0793
	(0.105)	(0.106)	(0.106)	(0.106)	(0.106)
reg7	-0.134	-0.131	-0.158	-0.129	-0.142
	(0.112)	(0.113)	(0.113)	(0.113)	(0.112)
reg8	-0.0224	-0.0172	-0.0243	-0.0128	-0.0250
	(0.109)	(0.110)	(0.109)	(0.110)	(0.109)
reg9	-0.145	-0.142	-0.150	-0.136	-0.149
	(0.108)	(0.110)	(0.110)	(0.110)	(0.110)

Employed	0.0398	0.0439	0.0360	0.0374	0.0313
	(0.118)	(0.118)	(0.119)	(0.119)	(0.119)
Self-employed	0.234	0.245	0.242	0.240	0.248
	(0.183)	(0.184)	(0.186)	(0.185)	(0.185)
Retired	0.0303	0.0394	0.0417	0.0353	0.0143
	(0.151)	(0.151)	(0.150)	(0.152)	(0.151)
75000<Assets<224999	0.131***	0.126***	0.116**	0.128***	0.122**
	(0.0478)	(0.0481)	(0.0483)	(0.0481)	(0.0482)
224500<Assets<449999	0.222***	0.217***	0.214***	0.218***	0.214***
	(0.0328)	(0.0330)	(0.0330)	(0.0330)	(0.0330)
450000<Assets	0.260***	0.254***	0.243***	0.245***	0.240***
	(0.0290)	(0.0291)	(0.0292)	(0.0292)	(0.0293)
12000<Income<19999	-0.0130	-0.0171	-0.0122	-0.00961	-0.0114
	(0.0461)	(0.0461)	(0.0465)	(0.0462)	(0.0465)
20000<Income<29999	0.0286	0.0253	0.0233	0.0296	0.0291
	(0.0304)	(0.0304)	(0.0306)	(0.0305)	(0.0307)
Income>30000	0.0734***	0.0667**	0.0741***	0.0705***	0.0775***
	(0.0270)	(0.0271)	(0.0273)	(0.0272)	(0.0274)
Borrowing	-0.176	-0.160	-0.140	-0.159	-0.141
	(0.228)	(0.230)	(0.226)	(0.232)	(0.228)
0<Saving<999	0.101**	0.101**	0.106**	0.104**	0.107**
	(0.0418)	(0.0420)	(0.0423)	(0.0421)	(0.0421)
1000<Saving<4999	0.126***	0.124***	0.126***	0.122***	0.123***
	(0.0264)	(0.0266)	(0.0266)	(0.0266)	(0.0266)
Saving>5000	0.117***	0.113***	0.115***	0.113***	0.115***
	(0.0256)	(0.0256)	(0.0259)	(0.0257)	(0.0260)
NR(Saving)	-0.0863	-0.0932	-0.119	-0.0726	-0.0875
	(0.303)	(0.300)	(0.300)	(0.302)	(0.302)
NR(Assets)	0.144	0.150	0.133	0.138	0.136
	(0.145)	(0.147)	(0.148)	(0.148)	(0.148)
NR(Income)	0.0637	0.00170	0.0625	0.00760	0.0651
	(0.474)	(0.480)	(0.472)	(0.488)	(0.472)
NR(RA)	-0.752**	-0.735**	-0.729**	-0.730**	-0.737**
	(0.336)	(0.335)	(0.332)	(0.334)	(0.331)
NR_sC72	0.0260	0.0140	0.0471	0.00796	0.0726
	(0.309)	(0.307)	(0.302)	(0.312)	(0.301)

NR(% SC Particip.)					0.00819
					(0.124)
NR(% SC Inform.)					-0.152
					(0.123)
DK(% SC Particip.)					6.979**
					(3.367)
DK(% SC Inform.)			0.0216		
			(0.121)		
NR(% OC Inform)			-0.167		
			(0.121)		
NR(% FC Inform)			1.347		
			(3.214)		
DK(% FC Inform.)				0.143	
				(0.0869)	
NR(% FC Particip.)				0.0126	
				(0.0849)	
DK(% FC Particip.)		0.0667			
		(0.0874)			
NR(% OC Particip.)		-0.0614			
		(0.0859)			
Constant	-1.056***	-1.107***	-1.119***	-1.170***	-1.153***
	(0.288)	(0.296)	(0.302)	(0.295)	(0.300)
Log-likelihood	-1223	-1214	-1202	-1206	-1203
LR χ^2 (p-value)	396.1	401.7	435.4	419.0	422.7
Pseudo R^2	0.154	0.160	0.168	0.166	0.168
Observations	2,525	2,525	2,525	2,525	2,525

Standard errors in parentheses, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Source: authors' calculations on merged TNS 2014 & 2015 dataset.

Table 10: Specifications (13) and (14). Probit conditional marginal effects of covariates on the share of all financial wealth invested in the stock marke, full tablet.

VARIABLES	(1) % FW	(2) % FW	(3) % FW	(4) FW	(5) % FW
% SC Inform.		0.234**			
		(0.0973)			
% FC Inform.			0.142**		
			(0.0575)		
% OC Inform.			0.00784		
			(0.100)		
% SC Particip.				0.277***	
				(0.0977)	
% FC Particip.					0.150**
					(0.0599)
% OC Particip.					0.147
					(0.105)
Expec R	36.33***	35.20***	33.40***	34.49***	32.94***
	(11.56)	(11.54)	(11.52)	(11.53)	(11.53)
RA	-0.374*	-0.366*	-0.380**	-0.365*	-0.371*
	(0.192)	(0.192)	(0.191)	(0.192)	(0.191)
35<Age<50	9.150***	9.461***	8.720**	8.955**	8.374**
	(3.510)	(3.504)	(3.508)	(3.504)	(3.505)
50<Age<65	12.98***	13.46***	13.24***	13.36***	13.36***
	(3.650)	(3.652)	(3.645)	(3.647)	(3.644)
Age>65	18.66***	18.91***	18.72***	19.01***	19.32***
	(5.293)	(5.289)	(5.285)	(5.284)	(5.283)
Male	5.261**	4.901**	4.633**	4.763**	4.507**
	(2.102)	(2.102)	(2.100)	(2.102)	(2.099)
Married	-7.645***	-7.434***	-7.597***	-7.364***	-7.390***
	(2.319)	(2.315)	(2.313)	(2.314)	(2.310)
Children at Home > 0	-2.678	-2.619	-2.459	-2.378	-2.340
	(3.026)	(3.021)	(3.013)	(3.020)	(3.015)
College or more	4.287*	3.716*	3.257	3.717*	3.199
	(2.253)	(2.254)	(2.262)	(2.253)	(2.259)
reg2	-6.331	-5.751	-6.219	-5.990	-6.009
	(4.968)	(4.961)	(4.949)	(4.952)	(4.942)
reg3	3.129	3.792	3.277	3.900	3.502
	(4.008)	(4.004)	(4.007)	(4.003)	(4.000)
reg4	-4.292	-3.453	-4.272	-3.450	-4.013
	(4.262)	(4.261)	(4.260)	(4.252)	(4.252)
reg5	4.602	4.961	4.739	4.769	4.901
	(3.894)	(3.889)	(3.879)	(3.886)	(3.879)
reg6	-4.817	-4.187	-4.571	-4.323	-4.099
	(3.502)	(3.501)	(3.493)	(3.499)	(3.491)
reg7	-5.124	-4.971	-5.360	-5.005	-4.824
	(3.755)	(3.754)	(3.750)	(3.755)	(3.749)
reg8	-1.282	-0.917	-0.910	-0.923	-0.770
	(3.627)	(3.633)	(3.626)	(3.630)	(3.625)
reg9	-0.386	-0.249	-0.177	-0.00885	-0.0699
	(3.552)	(3.547)	(3.540)	(3.546)	(3.539)

Employed	0.260	0.506	0.385	0.0758	0.157
	(4.095)	(4.091)	(4.083)	(4.085)	(4.078)
Self-employed	-0.706	-0.126	-0.131	-0.710	-0.131
	(6.360)	(6.348)	(6.329)	(6.340)	(6.316)
Retired	-4.278	-3.737	-3.830	-3.927	-4.563
	(5.030)	(5.027)	(5.015)	(5.020)	(5.011)
75000<Assets<224999	4.972***	4.779***	4.601***	4.794***	4.703***
	(1.626)	(1.624)	(1.621)	(1.622)	(1.619)
224500<Assets<449999	7.669***	7.535***	7.436***	7.504***	7.457***
	(1.112)	(1.110)	(1.108)	(1.109)	(1.108)
450000<Assets	8.048***	7.870***	7.587***	7.658***	7.470***
	(0.966)	(0.964)	(0.966)	(0.967)	(0.967)
12000<Income<19999	-3.855**	-4.048**	-3.730**	-3.877**	-3.777**
	(1.639)	(1.638)	(1.635)	(1.640)	(1.635)
20000<Income<29999	-0.229	-0.368	-0.343	-0.234	-0.227
	(1.063)	(1.062)	(1.061)	(1.062)	(1.061)
Income>30000	0.660	0.431	0.705	0.544	0.754
	(0.905)	(0.905)	(0.903)	(0.904)	(0.904)
Borrowing	-13.09	-12.44	-12.33	-12.60	-12.14
	(8.830)	(8.808)	(8.745)	(8.829)	(8.724)
0<Saving<999	2.169	2.135	2.312	2.130	2.285
	(1.433)	(1.431)	(1.430)	(1.431)	(1.428)
1000<Saving<4999	3.556***	3.462***	3.499***	3.441***	3.436***
	(0.903)	(0.901)	(0.900)	(0.900)	(0.899)
Saving>5000	2.342***	2.179***	2.216***	2.191***	2.184***
	(0.845)	(0.844)	(0.844)	(0.844)	(0.842)
NR(Saving)	-1.965	-2.382	-2.857	-2.269	-2.252
	(10.89)	(10.88)	(10.81)	(10.88)	(10.82)
NR(Assets)	13.61**	13.73**	13.22**	13.46**	13.17**
	(5.495)	(5.480)	(5.468)	(5.478)	(5.465)
NR(Income)	-197.2	-197.1	-193.2	-196.0	-193.0
	(0)	(0)	(0)	(0)	(0)
NR(RA)	-9.116	-8.822	-8.824	-8.768	-8.443
	(10.92)	(10.89)	(10.86)	(10.89)	(10.85)
NR_sC72	-14.38	-14.63	-14.80	-14.70	-14.15
	(12.13)	(12.07)	(12.22)	(12.10)	(12.18)

NR(% SC Particip.)					-2.435
					(4.225)
NR(% SC Inform.)					-4.291
					(4.175)
DK(% SC Particip.)					149.6
					(106.5)
DK(% SC Inform.)			-4.236		
			(4.167)		
NR(% OC Inform)			-6.527		
			(4.120)		
NR(% FC Inform)			11.04		
			(101.7)		
DK(% FC Inform.)				0.991	
				(2.850)	
NR(% FC Particip.)				-2.733	
				(2.724)	
DK(% FC Particip.)		1.373			
		(2.883)			
NR(% OC Particip.)		-2.367			
		(2.783)			
Constant	-37.00***	-37.53***	-35.36***	-36.88***	-36.72***
	(9.089)	(9.264)	(9.331)	(9.249)	(9.311)
Log-likelihood	-3643	-3637	-3634	-3635	-3632
LR χ^2 (p-value)	358.0	370.3	376.3	373.9	379.5
Pseudo R^2	0.0468	0.0484	0.0492	0.0489	0.0497
Observations	2,294	2,294	2,294	2,294	2,294

Standard errors in parentheses, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.
Source: authors' calculations on merged TNS 2014 & 2015 dataset.

Table 11: Specifications (13) and (14). Tobit conditional marginal effects of covariates on the share of all financial wealth invested in the stock market, full table.