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INFORMATIVE SOCIAL INTERACTIONS*

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ABSTRACT. We collect survey data from a representative population sample to examine whether informative social interactions significantly influence perceptions of past returns, expectations, participation and exposure to a widely known financial instrument in a developed economy with multiple information sources. Respondents report perceptions about peers with whom they discuss financial matters, their social circle, and the population. We provide evidence for the presence of an information channel through which social interactions influence perceptions and expectations about stock returns, stock market participation and portfolio share. We find only mixed evidence of mindless imitation of peers, permeating fewer layers of financial behavior.

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

JEL CODES: G5, D12, D83, D84, G11.

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1. INTRODUCTION

Financially developed economies repeatedly experience episodes in which patterns of behavior spread rapidly through the population and then culminate in dramatic adverse events. Examples of such episodes include 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 more recent global financial crisis. In the face of such important events, it is natural to ask: what is the role of social interactions in the spread of financial behavior and what are the main channels through which they operate? Two channels are of particular interest. The first is direct flow of information and knowledge between individuals, while the second is imitation of peers, either mindful or mindless. Imitation is mindful when peers are perceived to be knowledgeable or well-informed and thus their actions convey useful information. It is mindless when the perceived actions of peers influence the subject's actions without conveying any intrinsic financial information. Being able to disentangle informative social interactions, namely the exchange of information and mindful imitation, from mindless imitation is fundamentally important for understanding the spread of financial behavior and aggregate macroeconomic outcomes, as well as for the design and conduct of public policy.

In this paper, we focus on the influence of peers on individuals' subjective perceptions of recent past asset returns, subjective expectations of future returns, asset market participation decisions, and conditional exposure to financial risk. We are particularly interested in examining whether there is a significant role for *informative* social interactions with regard to a widely known and used financial instrument (stocks) in a financially developed economy (France) with a mature stock market and with multiple possible sources of information for individuals. In such a setup, is there room for social interactions with peers to contribute to the accuracy of perceptions of the past and expectations of the future, as well as to stock market participation and exposure? Or should we be thinking of informative social interactions as plausibly relevant only for setups where brand new financial products are introduced, peers are the only source of information, and alternative financial instruments are limited or non-existent?

To this end, we conduct a survey of a representative sample of French households, where we elicit their perceptions of past and expectations of future stock returns, as well as their own perceptions about their peers' information and participation, both in their overall social circle and in an inner *financial circle* with whom they choose to discuss financial matters. Our econometric findings, both in baseline analysis and in a number of robustness exercises, support a systematically positive role of social interactions in improving the accuracy of individuals' stock market expectations about future returns, which runs through their positive influence on the accuracy of perceptions of past returns. They also point to further relevance of informative social interactions for stock market participation and conditional portfolio shares, controlling for subjective stock market expectations. While our analysis allows for possible presence of mindless imitation of perceived stockholding among the respondents' outer social circle, with whom they do not purposefully discuss financial matters, it finds at best mixed evidence for such

presence. We also show that this empirically derived footprint of informative social interactions is consistent, under reasonable assumptions, with a theoretical model of a large, anonymous, and efficient stock market, where individuals condition their expectations on equilibrium asset prices: in such an environment, informative social interactions survive in equilibrium by reducing the posterior variance of returns.

In order to provide theoretical underpinnings for our empirical analysis, we model direct communication and information dissemination between individuals, within a large efficient financial market. Specifically, we extend the work of Ozsoylev and Walden (2011) to allow for individual heterogeneity in both risk preferences and signal precision, in line with available empirical evidence. Individuals receive private signals about asset returns, as well as publicly available information from equilibrium asset prices, and locally available information from their peers, friends and acquaintances, to whom they are connected through a well-defined information network. A key prediction of the model is that individuals with higher risk-adjusted ‘connect- edness’, i.e. those with more and/or more informative social interactions, invest more in risky assets, in response to good signals and for given risk tolerance. This is because well-connected individuals pool both more and more precise privately received signals from individuals they are acquainted with, increasing the precision of their conditional stock market return expectations.

We collect novel survey data from a representative sample by age, asset classes and wealth of the population of France in December 2014 and May 2015. The survey questionnaire provides measures of stock market participation and risky portfolio share, risk attitudes, questions designed to obtain quantitative measures of relevant social network characteristics, connectedness within the network of peers, perceptions regarding peers, as well as probabilistically elicited subjective expectations of future stock market returns and perceptions of recent past returns. The questionnaire also contains a rich set of covariates for socioeconomic and demographic controls, own and social preferences, constraints, and access and frequency of consultation of information sources.

We elicit perceptions of respondents regarding the stock market behavior and information of three circles around the respondent: the financial circle, i.e. peers with whom they discuss financial matters; the overall social circle of friends and acquaintances; and the overall population in the country. We find that the financial circle of peers whom the respondents trust enough to discuss financial matters, is typically small relative to the social circle. On average it contains three to five people, relative to an average size of 53 people for a respondent’s social circle. As we do not control for average actual peer behavior but for respondents’ *perceived* peer behavior, we can circumvent Manski’s (1993) reflection problem that arises when social interactions are identified empirically from linear-in-means econometric specifications.¹ Given the anonymous nature of stockholding and trading, our analysis is not limited by the fact that we do not trace the actual network structure (De Paula, 2016), as this is an inherent feature of the stock market in view of which stockholding behavior is determined.

¹See Blume, Brock, Durlauf and Ioannides (2011).

In our baseline econometric analysis, we find that respondents who perceive their financial circles to be more informed or more widely participating in the stock market report perceptions of past returns closer to the truth, controlling for a wide array of respondent characteristics and other perceptions. Interestingly, the extent to which respondents perceive their financial circle to be informed about or participating in the stock market is related to the accuracy of their subjective expectations of returns only through improved perceptions of (recently realized) returns. These findings argue against the view that individuals simply mimic the optimism of those they interact with, without in fact becoming better informed about the stock market.

Although our emphasis is on establishing the relevance of informative social interactions, we also find mixed evidence that respondents are influenced by perceived stock market participation among their outer social circle, even though they do not purposefully discuss financial matters with them. Any such effect does not run either through perceptions or expectations, but controlling for expectations. This points to the conclusion that mindless imitation, if present, does not permeate as many layers of the stockholding decision as do informative interactions with the financial circle.

We employ a number of robustness checks that corroborate our main findings. First, we allow for endogenous formation of an inner financial circle, with whom the respondent chooses to discuss financial matters, and for potential correlation between unobserved factors influencing this decision and the accuracy of return perceptions or expectations; or unobserved factors influencing the decision to form a financial circle and to expose oneself to stockholding risk. Our findings on the relevance of perceived information or participation among members of the financial circle remain robust, and this also holds for our baseline results on the outer social circle. Moreover, we cannot reject the hypothesis of independence of unobserved factors influencing the decision to form a financial circle and those influencing perceptions, expectations, or behavior.

Second, we consider the possibility that our findings merely reflect a tendency of respondents and the members of their financial circles to be characterized by common preferences or to be subjected to common shocks. Such factors could be shifting both the proxy for peer effects and the outcome variables, thus inflating the estimated size of the peer effects. To produce the particular pattern we find, of significant effects of the financial circle and insignificant or mixed effects of the outer social circle, outer social circle members should then be sufficiently less similar in preferences and less subject to common shocks with the respondents than the inner financial circle is. In order to address this possibility, We conduct placebo tests, reshuffling responses on the financial and the outer circle, the population, and non-response dummies among respondents in the same age, education and location group. When we do so, we no longer find statistically significant effects of the financial or any other circle on the accuracy of perceptions about past stock returns and expectations of future returns, nor on stockholding behavior, at the extensive or intensive margin. We obtain similar results when we consider the possibility that common preferences or common shocks apply to groups that share a larger number of characteristics

(age, education, region of residence, marital status, occupational status, and having children). Further analysis with instrumental variable estimation results in substantially larger estimates of coefficients on the perceived degree of information or participation in the financial circle and also fails to reject the null of exogeneity.²

Third, we consistently find that the perceived degree of information in the outer circle is insignificant for perceptions, expectations and behavior. Since respondents discuss financial matters with their financial circle but form their perceptions of outer circle finances based only on casual or incidental remarks, it is plausible that they are much less certain about the outer circle. Could our insignificant estimates on information in the outer circle be an artifact of attenuation bias, even in the presence of significant coefficients on outer circle stock market participation? When we instrument responses regarding the outer circle with respondent perceptions regarding the overall population, which are actually quite consistent with population statistics, we find insignificant coefficients on both perceived information and participation in the outer circle. Importantly, the coefficients on the financial circle remain significant even in this case.

Fourth, we also consider reverse causality, namely that respondents who participate in stocks or are more exposed to stockholding risk may be more likely to persuade themselves that a higher number of their peers also participate in stocks. If perceptions of stockholding among peers are driven by such ‘feel-good’ considerations, it is hard to see why they are also associated with more accurate perceptions and expectations of stock returns, and why they don’t extend to perceptions of participation in the overall population. It is difficult to reconcile such an argument with our findings regarding insignificant perceptions of participation in the overall population, or with the tendency of those who perceive more of their peers as stockholders to be more accurate in their perceptions of past stock market movements and in their expectations of future movements. It is also not clear how the argument applies to perceptions of information among peers, as those who understand returns better and who are more likely to engage in stockholding are also in a better position to assess the degree of information possessed by their financial circle.

Our work can be placed in the rapidly growing literature in household finance, but it relates to various strands of literature: peer effects, subjective expectations, information flows and social comparisons, financial literacy, and social networks.³ The part of our analysis that studies peers influencing expectations, which then feed into actions, is most closely related to Bailey, Cao, Kuchler and Stroebel (2016), and Giglio, Maggiori, Stroebel, and Utkus (2020). The aspect that relates to accuracy of household perceptions of the past and expectations about future returns, financial knowledge, information, and their transmission, links to relevant

²Our findings on the possible relevance of common preferences or shocks are also consistent with the analysis of Giglio, Maggiori, Stroebel, and Utkus (2020), who use a hybrid dataset from Vanguard in the US and find that expectations of future returns are not to be traced primarily to demographic characteristics but to heterogeneous and persistent individual fixed effects; and that these beliefs are not changing much over time in response to time variation in average expected returns.

³An overview of research in household finance, including the placement of peer effects within its corpus, is provided in Gomes, Haliassos, Ramadorai (2020).

literature on financial literacy (Lusardi, Michaud and Mitchell, 2016; Campbell, 2016; Haliassos, Jansson and Karabulut, 2020).⁴ As we analyze peer effects on financial behavior through information dissemination and social comparisons, we link to the relevant peer effects literature in financial behavior (Kaustia and Knüpfer, 2012; Banerjee, Chandrasekhar, Duflo and Jackson, 2013; Bursztyn, Ederer, Ferman and Yuchtman, 2014; Georgarakos, Haliassos and Pasini, 2014; Beshears, Choi, Laibson, Madrian and Milkman, 2015; Girshina, Mathae and Ziegelmeier, 2019; Ouimet and Tate, 2017), which builds upon the seminal papers of Duflo and Saez (2002, 2003) and Hong, Kubik and Stein (2004). Part of our work studies the nature and role of subjective expectations elicited in surveys. The promise of survey-based expectations and their link to financial and other types of behavior has been discussed in Hurd (2009), Greenwood and Schleifer (2014), and Manski (2017), while its important implications for aggregate behavior were addressed in Carroll (2003). Our study also relates to the literature on the effects of social imitation and influence on financial behavior in competitive markets, as part of the larger literature on social and information networks (see Jackson, 2008).

Methodologically, our empirical analysis is based on survey elicitation, and it complements both administrative data and experimental research on social learning and social utility in a number of important dimensions. Administrative data offer clear information on location and thus geographical proximity with potential peers, as well as detailed information on participation and holdings (see, for example, Kaustia and Knüpfer, 2012; Girshina, Mathae and Ziegelmeier, 2019; Haliassos, Jansson and Karabulut, 2020). However, administrative data do not include information on subjective expectations, perceptions of past stock returns, or perceptions of peer information or behavior. Experiments in the field or in the lab are able to control fully the information flow by focusing on a previously unknown product, knowing the precise network structure, and being able to control the exogenous flow of information to the agent, which takes the form of substantive information first and then information on whether peers hold the instrument or not. This allows a clean separation of social learning from social utility and an assessment of the relative importance of the two. Two important examples are Banerjee, Chandrasekhar, Duflo and Jackson (2013), who study a newly introduced micro-finance program in rural India, and Bursztyn, Ederer, Ferman and Yuchtman (2014), who conduct a field experiment in collaboration with a Brazilian brokerage firm for a brand new financial product. Both studies conclude that information on a new product provided through peers is important, but they differ on the importance of the social utility channel.⁵

Our survey-based study complements administrative data studies by shedding light on subjective expectations and perceptions and the role peer interactions play in forming those and financial behavior. It also complements experimental approaches by asking whether social learning and social utility matter in the case of well-established products, such as stocks, in a

⁴For an extensive survey of the very broad field of financial literacy, see Lusardi and Mitchell (2014).

⁵The former paper finds that, once informed, an agent's decision to participate in the program is not significantly influenced by the fraction of her friends participating; the latter finds that for a new product both motives are important in individual financial decision making, but the social learning channel is relatively more important than the social utility channel among more sophisticated investors.

decentralized and anonymous market, such as the French stock market, with multiple potential sources of information that individuals can tap, including peers. This is highly relevant but not obvious. In the case of established financial products and developed environments, the incremental impact of information that individuals may or may not choose to obtain from peers can be limited, as a lot may be known already and peers may not be the most knowledgeable sources. Our findings consistently support the view that, even in such cases, the levels of information and exposure to the product among the respondent's financial circle contribute to the accuracy of return perceptions and expectations, and to the decisions to hold the premium asset and to adopt a higher risky portfolio share.

The paper is structured as follows. The next section presents the theoretical framework and derives key predictions. Section 3 discusses how the social circle is decomposed into a financial circle and an outer circle, and the links of each to informative social interactions and mindless imitation. Section 4 describes the survey design and the data. Section 5 presents the baseline empirical results, and section 6 the results of robustness checks. Section 7 concludes.

2. THE MODEL

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

There are two assets, one risky (stock) and one risk free (bond). The payoff of the risk free asset is 1. The payoff of the risky asset follows a normal distribution $X \sim N(\bar{X}, \sigma^2)$ and its price is p . The supply of stocks is random and is given by $Z_n = nZ$, where $Z \sim N(\bar{Z}, \Delta^2)$ and $\bar{Z} > 0$.⁶ The final wealth of the agent is

$$\omega_i = \omega_{0i} + D_i(X - p), \quad (1)$$

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 . We assume constant absolute risk aversion (CARA) preferences $u(\omega_i) = -e^{-\rho_i \omega_i}$, where ρ_i is the absolute risk aversion of agent i . Agent i thus solves the problem

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

Therefore,

$$D_i^* = \frac{\mathbb{E}[(X - p) \mid \mathcal{I}_i]}{\rho_i \mathbb{V}[X \mid \mathcal{I}_i]}. \quad (3)$$

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

⁶See Easley, O'Hara and Yang (2013) for discussion on positive supply of risky assets and liquidity traders.

the signals of the agents, $\mathbb{V}[X|\mathcal{I}_i]$, to reflect the fact that agents may have more or less precise information about the risky asset for exogenous reasons.

Agents 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/her 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/her own signal with those of his/her neighbors to generate a payoff signal x_i , by averaging the signals of his/her 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 .⁷ From the perspective of agent i , when pooling all the signals from his/her neighbors, he/she then puts more weight on agents with more precise signals and less weight on those with less precision.⁸ 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 $\Sigma = \text{diag}\{s_1^2, \dots, s_n^2\}$. We note that G represents a weighted and directed network. The pooled payoff signal x_i for agent i is:

$$x_i = \frac{\sum_{k \in R_i} y_k}{d_i} \equiv \frac{\sum_{k=1}^n g_{ik} y_k}{\sum_{k=1}^n g_{ik}} = X + \frac{\sum_{k=1}^n g_{ik} \epsilon_k}{\sum_{k=1}^n g_{ik}}. \quad (4)$$

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. Given the information network, investors' information sets are defined by

$$\mathcal{I}_i = \{x_i, p\}, \forall i = 1, \dots, n \quad (5)$$

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

Next, let

$$k_i = \sum_{k=1}^n \frac{a_{ik}}{s_k^2} \quad (6)$$

⁷We can also assume it to be the *relative* precision of the signal of agent j , i.e. the precision of j 's signal over the precision of i 's signal. This is a more attractive assumption, but complicates unnecessarily the mathematical expressions of the assumptions needed in deriving the optimal demand function, without affecting the formal expression of our econometric specification.

⁸Proportional weighting as a function of signal precisions typically obtains in models of Bayesian learning from others, but also in recent models of contagion, e.g. Burnside, Eichenbaum and Rebelo (2016).

be the *connectedness* of investor i . This is a generalization of the well known concept of degree, or strength, which counts the number of links of a network node. Under a set of assumptions on the asymptotic nature of the network structure as the number of investors n grows, we extend and generalize Theorem 1 of Ozsoylev and Walden (2011). The set of assumptions and the precise statement of the Theorem can be found in Appendix A. Broadly speaking, the assumptions require that the information network is sparse, i.e. that the strength of connections between agents is of the same order as the number of nodes, and that no agent is informationally superior in the large financial market (as $n \rightarrow \infty$). The average connectedness β of the economy-wide information network as the economy grows, is defined via the assumption that

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

which imposes that the average risk-adjusted node strength is finite. Then, we show that there exists a linear noisy rational expectations equilibrium as $n \rightarrow \infty$, such that with probability one the risky asset price converges to

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

where

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

and $\hat{\rho}$ denotes the finite harmonic mean of risk aversions of all agents in the population (see Assumption 3, in Appendix A).

In determining their 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 $n \rightarrow \infty$, the expected return for an investor i is given by

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

where $k_i^* = \lim_{n \rightarrow \infty} k_i$. This suggests that larger connectedness k_i^* implies that investors' expectations react more strongly to their pooled signal x_i . Similarly, the equilibrium posterior variance of returns of investor i is given by

$$\mathbb{V}(X|\mathcal{I}_i) = \left(\frac{1}{\sigma^2} + k_i^* + \frac{\beta^2}{\Delta^2} \right)^{-1}, \quad (9)$$

implying that investors' risk exposure, as measured by the conditional variance of returns, *decreases* the more/better connected they are, as measured by agents' connectedness k_i^* . That this is consistent with Bayesian learning from peers, can be seen from rearranging (8) as

$$\mathbb{E}(X|\mathcal{I}_i) - \bar{X} = \psi(k_i^*)(x_i - \bar{X}) \quad (10)$$

where $\psi(k_i^*) \equiv \frac{k_i^* \sigma^2 \Delta^2}{k_i^* \sigma^2 \Delta^2 + \Delta^2 + \sigma^2 \beta^2} = k_i^* \left(\frac{1}{\sigma^2} + k_i^* + \frac{\beta^2}{\Delta^2} \right)^{-1}$ denotes the weight signal x_i is given in equilibrium by agent i relative to the prior belief \bar{X} , which increases with agent i 's connectedness

k_i^* , i.e. $\psi'(k_i^*) > 0$. Therefore, agents' posterior expectations of the asset payoff, $\mathbb{E}(X|\mathcal{I}_i)$, are revised more strongly in the direction of the signal, x_i , (i) the further away their prior asset payoff expectations are from the signal, $(x_i - \bar{X})$, and (ii) the better/more connected agent i is, $\psi(k_i^*)$. Moreover, in equilibrium, the demand for the risky asset by an agent i , (3), can be expressed as:⁹

$$D_i^* \equiv \frac{1}{\rho_i} \left(\frac{1}{\sigma^2} + k_i^* + \frac{\beta^2}{\Delta^2} \right) (\mathbb{E}(X|\mathcal{I}_i) - p) \quad (11)$$

Expressions (8) and (11) will guide our empirical investigation of informative social interactions. Expression (11) suggests that there are two ways in which individual connectedness k_i^* is important for investor's i demand for the risky asset: first there is an indirect effect via the expected return, since k_i^* affects $\mathbb{E}(X|\mathcal{I}_i)$ in (8), and second, a direct positive effect of risk-adjusted connectedness k_i^*/ρ_i appearing in the first parenthesis of (11). The former captures the higher relative weight attributed to more/better informed peers when forming the expectation of a stock market return, common in work on Bayesian learning from peers. The latter captures the reduction in agents' posterior variance of expected returns, (9), obtained in equilibrium by agents that are more and/or better connected, adjusted by the agent's risk aversion.

Equilibrium asset prices and optimal demand for risky assets by individuals are parametrized by a range of model characteristics. Here, our main focus is on two of those, namely connectedness of individuals and risk attitudes, which we discuss in turn. First, the model predicts that higher individual connectedness makes agents more willing to invest in risky assets in response to good pooled signals. In addition, higher individual connectedness k_i^* may be the result of two effects: (i) a larger number of acquaintances (i.e. larger number of agents for which of $a_{ij} \neq 0$) and/or (ii) higher signal precision of the signals that individual i pools from her/his social interactions. Both effects imply that the more informative one's social interactions are (i.e. as the precision of an individual's pooled signals improves), the lower is the posterior variance of returns and hence, the higher the fraction of wealth that the agent is willing to place in the risky asset, in response to good signals. This is the *information effect* from informative social interactions for which we seek evidence in our empirical analysis. Second, risk preferences matter for equilibrium demand for information: a given connectedness (which measures how informed an agent is) has more value when the agent's risk aversion is lower, because less risk averse agents can expect to benefit more from investing in the risky asset, as recently uncovered by Cabrales, Gossner and Serrano (2013, 2017).¹⁰

We also highlight here that both the expressions for expected returns (8) and equilibrium

⁹In Appendix A, Theorem 1, we show that further replacing expression (8) in expression (11) yields the equilibrium asymptotic demand for the risky asset by agent i ,

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

¹⁰Heterogeneity in risk preferences is what would drive trade in assets in this model were information homogeneous across investors. Less risk averse investors would also be willing to pay more for informative private signals, as recently shown by Cabrales et al. (2013). As a result, less risk averse agents would be expected to have more/better informed connections, which creates the need to extend Ozsoylev and Walden's (2011) theorem to heterogeneity in risk aversion before seeking empirical validation of the model's predictions.

individual demands (11) only require knowledge about the economy-wide average connectedness β and the individual connectedness of investors, k_i^* , and not the exact general structure of the network. This is a very important feature of the theoretical framework for the design of our empirical strategy, because it allows us to sidestep known issues that arise from not knowing the exact network structure within a population. For our purposes, when designing the survey, a representative sample from a large population for which we can identify measures for k_i^* is sufficient for an empirical analysis of an information peer effect, and the two expressions (8) and (11) will be the basis of our empirical design and specifications.

3. THE SOCIAL AND FINANCIAL CIRCLES

Our assumption in the theoretical model is that respondents meet their peers and weight the information they obtain from them according to how reliable they perceive their peers to be. In real life, it is natural to think of respondents as deciding on whether to form a subset of their social circle, that we call “financial circle”, with which to discuss financial matters in the course of making financial choices. To the best of our knowledge, our survey is the first to elicit responses from individuals regarding the existence of such an inner financial circle, as well as perceptions regarding attributes of its members separately from the overall social circle of peers.

Now, a number of factors, both observable and unobservable, may enter the decision on whether to form a financial circle. These include the respondent’s assessment of information available in the overall social circle, as well as factors that correlate with the need for financial information from peers or with the willingness to acquire such information. Demographic characteristics, the size of financial resources, attitudes (such as risk aversion or trust), as well as perceived position among peers in terms of education, wealth, or professional standing can be relevant for the decision to form a financial circle. Factors relevant for this decision may be among the wide array of respondent characteristics observable to us, or may be unobserved. Furthermore, there may be correlation between unobserved factors influencing the decision to form a financial circle and those relevant for stockholding. Indeed, unobserved factors encouraging households to participate in the stock market may also encourage them to form a financial circle, precisely so as to facilitate choices related to stockholding.

In what follows, we will want to understand the levels at which informative social interactions with the financial circle operate. In principle, interaction with informed or participating peers can improve the accuracy of perceptions regarding past returns, expected future returns, and stockholding behavior. At each level, information or participation of peers can influence the outcome directly, in addition to any effect it may have had on the previous level. For example, our survey records significant heterogeneity in perceptions of past stock returns and in expectations of future returns, consistent with our modeling choice of a departure from full-information rational expectations. Interaction with informed or participating peers can sharpen the accuracy of respondent perceptions of past returns, which enter the determination of expected future returns, but may also have a direct further effect on expectations, controlling for perceptions of the past. In turn, interaction with informed or participating peers may be related to greater

stockholding participation or exposure because of its link to expectations, but may also have a further, direct influence beyond the expectational one. Our approach aims to uncover the presence of any such influences.

We have designed the questionnaire to elicit information from respondents regarding their perceptions of the share of informed and of participating peers in their circle of peers. It is important to stress that our data do not record actual shares of informed or participating peers, which may or may not be known to respondents, but shares *as these are perceived* by respondents who form expectations and decide on own stock market participation and exposure. We ask this information on two circles: the “financial circle”, i.e., those peers with whom the respondent discusses financial matters; and the “social circle”, i.e., the overall set of peers with whom the respondent interacts socially.

Two issues arise. First, the respondent chooses whether to have a financial circle or not, and this choice may be related to observed respondent characteristics, but also to unobserved factors potentially correlated with the respondent’s stockholding behavior, expectations, or perceptions of past returns. Our econometric analysis allows for possible correlation of factors that we do not observe, and finds no evidence of sensitivity of estimates to allowing for correlation, nor of the presence of such correlation.

Second, while interactions with informed or participating peers in the financial circle are “informative”, either because they entail information transfer or because they represent mindful imitation of trusted peers, respondents may also engage in “mindless imitation”, based on their perceptions regarding information or stockholding behavior of social circle members with whom they do not discuss financial matters (the “outer” circle). Although the emphasis of our project is on establishing the presence of informative social interactions, it is interesting to see if we can also find evidence for mindless imitation of perceived participation in the outer circle. Now, respondent perceptions about stock market information or participation in the outer circle are likely to be less precise, because respondents do not care to discuss financial matters with their outer circle or because they are prevented to do so by shame, embarrassment, or lack of trust. Absence of a systematic relationship to perceptions of the outside circle may be due to this imprecision, but a relationship may exist for respondents who have a clearer view of their outer circle. To shed some light on this issue, we designed the questionnaire to elicit respondent perceptions about the financial circle and the *overall* social circle. We then compute their implied perceptions regarding members of their outer circle. This indirect approach identifies respondents who effectively report outer-circle shares of informed or participating peers below zero or over 100%. To minimize the influence of confusion, we exclude such respondents from our estimation.¹¹ We also elicit respondent perceptions on population-wide shares of informed and participating households. In the baseline, we control for those in case they have an independent role beyond responses on the financial and outer circles. In a robustness exercise, we use them as

¹¹Exception is made of those inconsistencies that are attributed to rounding, a total of 19 observations. We have alternatively set both the direct response on the financial circle and the implied one for the outer circle to ‘missing observation’, and have introduced an inconsistency dummy variable (IC) to flag them, with comparable results.

an instrument for respondent perceptions of the outer circle to allow for the possibility that such perceptions are shaped by what people know or think about overall behavior in the country.

4. SURVEY DESIGN

In this section, we provide information about key aspects of the special survey questions and sample, with more detailed information relegated to Appendix B.

4.1. The sample. We added specifically designed questions to an ongoing survey of the French population administered by Taylor-Nelson Sofres (TNS). We use two linked questionnaires that were fielded in December 2014 and May 2015, respectively. The first contains questions that provide detailed information on risk attitudes, preferences, expectations and perceptions of stock market returns, in addition to wealth, income and socioeconomic and demographic characteristics for a representative sample of French households by age, wealth and asset classes. The follow-up questionnaire contains questions that specifically aim at gathering information about how respondents perceive their social and financial circles and their own position within them along a number of dimensions.

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 returned completed questionnaires, corresponding to a 92% response rate. The follow-up questionnaire in May 2015 was sent to the 2014 wave of 3,670 respondents, out of which we recovered a total of 2,587 completed questionnaires, corresponding to a response rate of 70.5%.

4.2. Eliciting perceptions and expectations of returns. We ask respondents to state their perceptions of the past and expectations of the future regarding a public non-manipulable event, namely the return on a buy-and-hold portfolio that tracks the evolution of the stock market index, CAC-40. Following Manski (2004) and the recent expectations literature, we use probability questions rather than eliciting point expectations.¹² Probability densities are elicited on seven points of the outcome space, to obtain more precise individual estimates of the relevant moments.

The perception of the past return, *Perc. R*, refers to a window of three years, while the expectation about the future return, *Expec. R*, refers to a five-year time window.¹³ In both cases, we can also compute deviations from the respective actual return. 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 and is consistent with observed household portfolio inertia in the overall population (e.g., Biliias, Georgarakos and Haliassos, 2010). Probabilistic elicitation of the most recent cumulative stock market return over a three-year horizon provides a quantitative

¹²In an early contribution, focused on older households from the 2004 wave of the U.S. Health and Retirement Study (HRS), Dominitz and Manski (2007) elicit probabilistically individuals' expectations of stock market returns inquiring about how 'well' the respondent thinks the economy will do in the year ahead.

¹³We use responses to questions C39 and C42 (from TNS2014) to generate variables *Expec. R* and *Perc. R* respectively.

measure of households' degree of awareness of recent stock market developments, to capture differences in information across households as well as the relationship between information and expectations, as in Coibion, Gorodnichenko and Kumar (2018).¹⁴

4.3. Perceptions of the financial and social circles. The size of the (*social circle*) and of the (*financial circle*) are obtained from the following survey questions, respectively:

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

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

Of the 2,587 respondents that returned the TNS2015 questionnaire, 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 also report that the average of the remaining half (i.e. not taking into account the zeros) is approximately 5 people. This constitutes evidence in support of our theoretical framework and predictions, which are relevant under the assumption of sufficient network sparsity, i.e. the network is not too dense in terms of number of links.

With reference to the theoretical model in Section 2, the answer of respondent i to question C1 provides an approximation to the respondent's degree, defined by $\sum_{j=1}^n a_{ij}$, where A is the adjacency matrix. Question D1 generates 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 . Question D1 leaves open the possibility that the respondent does not have an inner circle peers with whom to conduct financial discussions, and this choice is modeled explicitly in the later part of our empirical analysis. Respondents may be able to extract information (signals) about the stock market from the members of their financial circle, i.e. we assume 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 $g_{ij} = 0$. Characteristics of the social circle excluding the financial circle, namely the *outer circle*, can then be inferred (up to an allowable margin of error) from responses regarding the overall social circle and the inner financial circle. For notational convenience we use the abbreviations SC , FC , OC for the social circle, financial circle, and outer circle, respectively. Other abbreviations are summarized in Table 1.

Having defined the various peer circles, we elicit respondents' point perceptions about how many of their friends and acquaintances in the overall social circle and in the financial circle,

¹⁴Armantier, Nelson, Topa, Van der Klaauw and Zafar (2016) document substantial differences across households regarding the most recent US inflation rate, while Afrouzi, Coibion, Gorodnichenko and Kumar, (2015) examine the relationship between inflation expectations and perceptions of inflation in a sample of CE/FOs of New Zealand firms.

are informed about the stock market, as well as their corresponding perceptions about peers investing in the stock market.¹⁵ The exact wording of the questions is:

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 sent back the TNS2015 questionnaire, about 96% and 88% of respondents provided valid answers for questions C7 and D16, respectively.¹⁶ The cross-sectional average point estimates for the perceived percentage of the social and financial circle that invests in the stock market are 10.7% and 18.9%, respectively; while the corresponding figures for peers that follow the stock market are 12.6% and 20.5%, respectively. These questions define the variables *%SC Particip.*, *%FC Particip.*, *%SC Inform.* and *%FC Inform.* The corresponding perceived percentages of the outer circle can easily be obtained.¹⁷ Similarly, questions C6i and C6ii ask respondents about the proportion of the French *population* that invests and is informed about the stock market, respectively.¹⁸ Interestingly, the cross-sectional average for the subjective responses regarding the proportion of the French population investing in the stock market is remarkably close to the cross-sectional mean participation rate in our representative sample: 19.4 percent versus 21.7 percent, respectively.

We also ask respondents to place themselves relative to others in their circles, both social and financial. Respondents state how they see themselves in terms of wealth, education and professional standing relative to their peers (for details, see Appendix B).

4.4. Other variables. Respondents are asked to state their total financial wealth (excluding housing), and of this wealth, what share they invest in the stock market (directly or indi-

¹⁵Asking respondents to report how they perceive their peers has been successfully implemented by researchers at the Dutch National Bank and at the University of Tilburg (CentER Panel) in the Dutch National Bank Survey, because of its relevance both for respondent behavior and for overcoming the reflection problem identified by Manski (1993). The reflection problem refers to the impossibility of separately identifying the effect of peers' *choices* (endogenous or peer effects) from the effect of peers' characteristics (contextual effects) on individual outcomes, when individual and peers' choices are made simultaneously and as a function of common contextual factors. Instead of considering peers' actual choices, researchers can exploit the variation in individual perceptions about peers' choices, combined with individual perceptions about peers' characteristics (e.g. peers' information or respondents' relative standing in terms of education, wealth or professional status). See Blume et al. (2011, 2015) for additional details.

¹⁶In answering each of the questions, the respondent was also given the option '*I do not know*'. About 64% and 61% chose this option for questions C7i and D16i, respectively, while about 61% and 58% reported this option for questions C7ii and D16ii. Respective DK controls were included in the estimation.

¹⁷They are obtained from

$$\%OC \text{ Particip.} \equiv \frac{C1 \times C7i - D1 \times D16i}{C1 - D1}, \quad (12)$$

$$\%OC \text{ Inform.} \equiv \frac{C1 \times C7ii - D1 \times D16ii}{C1 - D1}. \quad (13)$$

¹⁸About 54% and 52% chose the option '*I do not know*,' (DK) for questions C6i and C6ii, respectively, while about 3.1% chose not to answer these questions, and are accordingly coded as 'non-responses,' (NR).

rectly). The latter defines the participation dummy variable $\Pr(\text{Stocks} > 0)$, and the demand for risky assets conditional on such participation, $\%FW$. In addition, we collect information on demographic characteristics (age, gender, marital status, number of children), elicited risk preferences (coefficient of absolute risk aversion), proxies for resources and constraints (educational attainment, employment status, assets, income, perceived borrowing constraints, and achieved liquid saving over the past year), and region of residence. Table 8 provides various summary statistics. Further definitions, exact question statements and detailed explanations on variables can be found in Appendix B.

5. BASELINE ESTIMATES

Consistent with our theoretical analysis, in which equilibrium depends on the connectedness, k_i^* , rather than on the precise identity of interacting agents, we employ measures of such connectedness in our empirical analysis. Specifically, we focus on whether and how expectations about future returns, perceptions of past returns, and stockholding behavior are influenced by the share of the relevant peer circle that the respondent considers informed about, or participating in the stock market, controlling for factors, such as risk aversion, that correlate with potential benefits from acquired information. We first present baseline estimates and we then conduct extensive robustness analysis to address potential concerns.

5.1. Errors in Subjective Return Expectations and in Perceptions. We begin our analysis by investigating the role that the presence of informed or participating peers plays in the formation of subjective expectations about future stock market returns, as well as of perceptions regarding past stock market performance. Specifically, we focus on whether respondents who report higher shares of informed or participating peers tend to exhibit smaller absolute errors in their stock return forecast (over the next five years); and/or smaller absolute errors in their perception of the past (three-year) return. We also ask whether the perceived presence of informed or participating peers continues to be systematically related to the size of forecast errors once we control for the error in perceived past returns.

Considerable recent interest in subjective expectations has its origins in early papers that documented both their role in stockholding behavior and their suprisingly large heterogeneity, despite their reference to a single stock market (see Dominitz and Manski, 2007; Kezdi and Willis, 2009; Hurd et al., 2011). Even more surprising is the heterogeneity in perceptions regarding recent stock market returns, that we also find in our sample (Arrondel et al., 2014).

Figure 1 shows historical monthly data of the French stock market index CAC-40, from March 1990 to June 2016. The index dropped by nearly 25% at the time of the sovereign-debt crisis during the second half of 2011. After that and as we get closer to the time that the two parts of the survey were fielded, the stock market index was steadily recovering. Both in late December 2014 and May 2015, the index was still below its dot-com and the Lehman brothers peaks, but had already recovered relative to the sovereign-debt crisis. Given the substantial turmoil experienced by the stock market index over the period prior to data collection, respondents

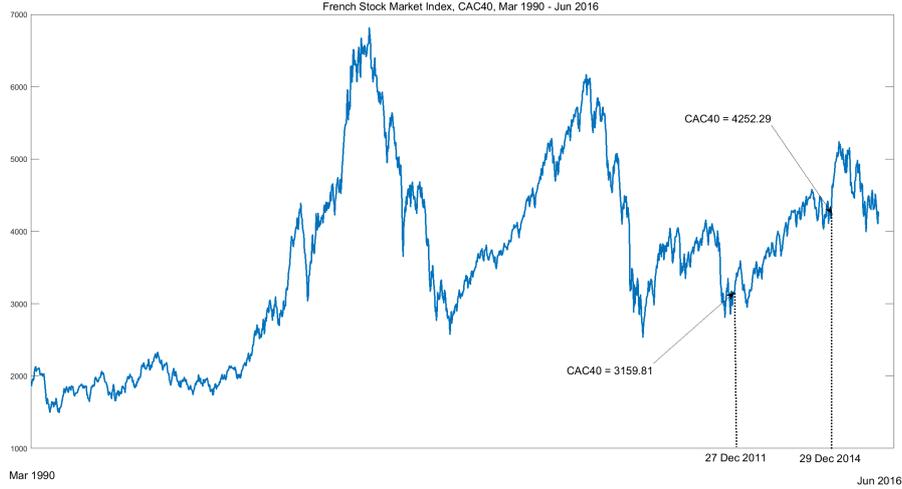


Figure 1: French stock market index, CAC 40, weekly data, 3 March 1990 - 27 June 2016. *Source:* Yahoo Finance.

are likely to have been exposed to considerable news coverage of the stock market evolution, and this makes the observed variation in perceptions and expectations all the more striking.

The actual stock market return over the three-year period in question (Dec 2011 - Dec 2014) was +34.57%, but the cross-sectional average perception of respondents regarding returns over the same period is equal to +3.6%. Figure 2 shows the actual 3-year returns from July 2014 to the June 2015. The average actual 3-year return in the second half of 2014 was +34.49%. Figure 2 also shows the annualized 3-year returns for the same period, which are still well above the average perceived returns, at an average value of 12.43%. Although this average perception gap in stock market returns seems too wide, it is consistent with rational inattention (Sims, 2003) and is in line with reported empirical findings on the inflation perception gap of households (Jonung, 1981; Armentier et al. 2016) and CE/FOs of firms (Coibion, et. al., 2018). The average cross-sectional subjective expectation of respondents regarding future five-year returns is equal to +1.6%. This deviates both from the immediate history prior to the interviews, as shown in Figure 2, and from the longer-run historical record.¹⁹

We have shown that even within an efficient competitive asset market, under certain conditions, information sourced from peers influences agents' expectations of returns. The recent empirical literature on subjective expectations of aggregate market outcomes (reviewed in Manski, 2017) has focused on the study of systematic patterns that explain the absolute value of deviations of subjective expectations from ex-post return realisations, $|R_{t+1} - F^i R_{t+1}|$ where $F^i R_{t+1} = E(X|\mathcal{I}_i) \equiv Expec. R_i$. In this spirit, guided by a first order approximation of (8) we

¹⁹Dimson, Marsh and Staunton (2008) report a historical (arithmetic) mean excess return (risk premium) in France for 1900-2005 of around 6% (per annum, p.a), but that figure was revised downwards by Le Bris and Hautcoeur (2010) to 2% p.a. when examining a longer time window (1870-2007), correctly weighting for stock market capitalization and adjusting for survivorship bias. Since we are asking respondents about the expected return over a five-year horizon, to be consistent with the estimate by Le Bris and Hautcoeur (2010) the cross-sectional mean should be 2% p.a. over a 5-year period, or around 10%, which is almost an order of magnitude larger than the cross-sectional mean expected return of 1.6%.

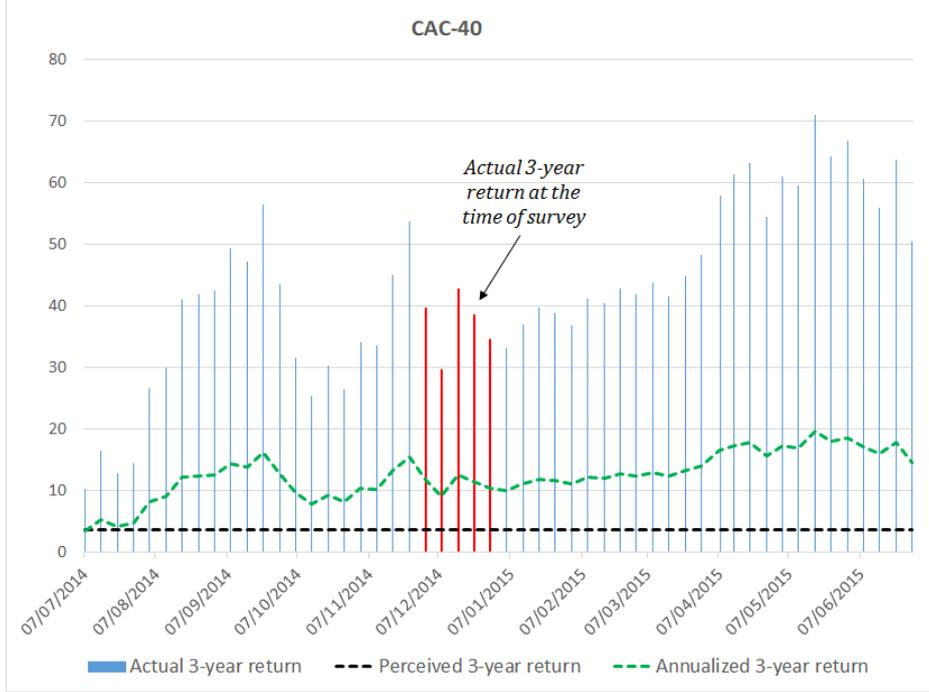


Figure 2: French stock market CAC 40, three-year stock market returns, weekly data, July 2014 to June 2015. The blue bars show cumulative 3-year returns and in particular, the red segment shows the actual cumulative 3-year return at the time that the survey was fielded, Dec 2014. The green dashed line shows the actual annualized 3-year returns and the black dashed line indicates the perceived 3-year return at the time that the survey was fielded. *Source*: Yahoo Finance.

propose the following two empirical specifications:²⁰

$$|R_{t+1} - Expec. R_t| = \kappa_0 + \kappa_1 k_i^* + \boldsymbol{\tau}_i \boldsymbol{\kappa} + e_i \quad (14)$$

and

$$|R_{t+1} - Expec. R_t| = \kappa_0 + \kappa_1 D_i^e + \boldsymbol{\tau}_i \boldsymbol{\kappa} + e_i, \quad (15)$$

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

We are able to control for a wide range of characteristics and attitudes of the household head. These include individual perceptions about the respondent's relative standing in terms of peer characteristics (professional status, education and total wealth), demographic characteristics (age, gender, marital status, number of children), elicited risk preferences (coefficient of absolute risk aversion), proxies for resources and constraints (educational attainment, employment status, assets, income, perceived borrowing constraints, and achieved liquid saving over the past year),

²⁰The derivation of (14) from our model in section 2 is included in Appendix A.

and region of residence.²¹ In all specifications, we also include dummies for item non-response and inconsistent responses, especially to the questions about perceived peer and population behavior.²²

Finally, we split respondents' social circle connectedness, k_i^* , (and behavior) into a financial circle, $k_{i,FC}^*$, and an outer circle, $k_{i,OC}^*$, controlling also for respondents' perceptions about overall population-level counterparts $k_{i,Pop}^*$:

$$|R_{t+1} - Expec. R_i| = \kappa_0 + \kappa_{1,FC} k_{i,FC}^* + \kappa_{1,OC} k_{i,OC}^* + \kappa_{1,P} k_{i,Pop}^* + \tau_i \boldsymbol{\kappa} + e_i, \quad (16)$$

and

$$|R_{t+1} - Expec. R_i| = \kappa_0 + \kappa_{1,FC} D_{i,FC}^e + \kappa_{1,OC} D_{i,OC}^e + \kappa_{1,P} D_{i,Pop}^e + \tau_i \boldsymbol{\kappa} + e_i. \quad (17)$$

Table 2 reports Huber-robust regression estimates for these two specifications under cols. (1) and (2), respectively. For both specifications we find that, relative to the corresponding perceived share of peers in the outer circle or in the population informed about (participating in) the stock market, a one standard deviation increase in the perceived informed (participating) share of peers in the respondent's financial circle (at a mean of 17.2 (16.6) percent) reduces the mean absolute forecast error by approximately -0.45 (-0.41) percentage points (or about a 1.5% (4.7%) reduction relative to the unconditional mean forecast error).

Recent literature on inflation expectations of households (e.g. Jonung, 1981; Armentier et al., 2016) or firms (Coibion et al., 2018) has found that beliefs about the past shape beliefs about the future.²³ We want to investigate whether our results in this first pass at estimating the relevance of the financial circle for expectational errors on stock returns reflects, partly or fully, its possible role in sharpening perceptions about recent past returns. To this end, we introduce as an additional control in econometric specifications (16) and (17) the absolute deviation of respondents' subjective perceptions about the most recent stock price growth over the last three years (nowcast or backcast, $B^i R_t$) from the actual realization, R_t , i.e. $|R_t - B^i R_t|$. Answers to question C42 in our survey enable probabilistic elicitation of respondents' perceptions about the most recent realized cumulative stock market return over a three-year period.²⁴

We focus on the mean of each respondent's subjective probability distribution over the

²¹Detailed variable definitions are to be found in Appendix B.

²²Controlling for item non response to those questions hardly affects the sign, size, and significance of the main coefficients of interest, namely on perceptions regarding peers. A similar robustness exercise in the presence of missing data can be found in Dimmock, et. al. (2016).

²³Note that this is conceptually different from 'extrapolative expectations', as recently documented in Bordalo et al. (2019). While there 'senior professional analysts' can be assumed to be all equally informed about realized returns, what the 'perceptions' literature initiated by Jonung (1981) documents is, precisely, that households (or firms) cannot be assumed to be equally informed about realized returns. Furthermore, ignorance about facts (as measured by respondents' perception gaps) explains beliefs about the future.

²⁴Armentier et al. (2016) have introduced past inflation in regressions of inflation expectations of households, and Coibion et al. (2018) have done so for inflation expectation of firms. Measuring individual information sets is difficult, even in experimental settings, but some progress has been made by extending Manski's (2004) probabilistic elicitation techniques to facts (as opposed to events). See, for example, Arrondel, Calvo-Pardo and Tas (2014), Afrouzi, Coibion, Gorodnichenko and Kumar (2016) and Coibion, Gorodnichenko and Kumar (2018). The exact wording of question C42, details about the construction of the variable as well as summary statistics can be found in Appendix B.

size of the realized three-year stock market return, which we denote $B^i R_t \equiv Perc. R_i$. Results reported in Table 2 under columns (3)-(5) show that the respondents' perception gap about facts, as measured by their mean perception error, is a strongly significant predictor of their forecast error, regardless of whether peer variables are included in the regression (columns 4 and 5) or not (column 3). This extends the results of the inflation literature to the stock returns literature. Strikingly, neither the share of informed peers nor the share of stockholders in respondents' financial circles retain their statistical significance in the presence of the respondent's mean perception error. This suggests that, if informative social interactions do influence subjective expectations of returns, the channel through which they operate is the extent to which they affect perceptions of realized returns.

To address this issue, we inquire into the potential relevance of the social interaction variables, k_i^* or D_i^e , for the absolute size of perception errors regarding recent past returns:

$$|R_t - Perc. R_i| = \eta_0 + \eta_{1,FC} k_{i,FC}^* + \eta_{1,OC} k_{i,OC}^* + \eta_{1,P} k_{i,Pop}^* + \boldsymbol{\tau}_i \boldsymbol{\eta} + \varrho_i, \quad (18)$$

or

$$|R_t - Perc. R_i| = \eta_0 + \eta_{1,FC} D_{i,FC}^e + \eta_{1,OC} D_{i,OC}^e + \eta_{1,P} D_{i,Pop}^e + \boldsymbol{\tau}_i \boldsymbol{\eta} + \varrho_i, \quad (19)$$

where ϱ_i is an individual zero-mean error term distributed normally conditional on covariates, $\boldsymbol{\tau}_i$ is a vector of individual characteristics.

The last two columns of Table 2 report significant (negative) estimates of the relationship between the absolute size of the perception error and either the perceived share of the financial circle informed about stocks (column (6)) or participating in stocks (column (7)). For both specifications we find that, relative to the share of peers in the outer circle or to the average person in the population informed about (participating in) the stock market, a one standard deviation increase in the mean informed (participating) share of peers in the respondent's financial circle of 17.8 (16.7) percent is associated with a reduction in the mean absolute perception error by approximately -0.91 (-0.76) percentage points (or about 2.9% (2.4%) relative to the unconditional mean backcast error).²⁵ Taken together, estimates in Table 2 suggest that, controlling for a wide range of household characteristics, informative interactions or mindful imitation of the financial circle tend to sharpen the accuracy of perceptions regarding the recent past return and, through that, increase the accuracy of return expectations.²⁶

5.2. Stockholding behavior. Our preceding analysis of subjective stock market expectations and perceptions has confirmed that connectedness to people more knowledgeable about

²⁵The results reported are robust to adopting Coibion et al.'s (2018) econometric specification not in 'error form'. Table A1 in the Online Appendix reports the results of Huber-robust regressions of expectations about future returns on perceptions of realized returns and the same individual controls.

²⁶The strongly significant positive coefficient on elicited risk aversion in the backcast error regressions is also consistent with an information interpretation. Those who are less willing to take risks are likely to have smaller exposure to stockholding, and therefore smaller benefits from sharpening their views regarding past or expected future stock returns. Other coefficients, omitted for brevity but available in the online appendix Table A2, are also consistent with an interpretation linked to information or financial knowledge. Controlling for retirement status, males, older and wealthier respondents tend to exhibit smaller backcast errors, while retirement status or being self employed per se are associated with larger backcast errors.

the stock market tends to reduce absolute deviations of subjective expectations and perceptions from realized returns. In this section, we examine our second prediction, i.e. that social interactions and connectedness increase the prevalence of stockholding and the degree of exposure to stockholding risk, beyond their indirect effect through stock market expectations.

Our starting point is the demand for investing in the stock market in expression (11). Reorganizing this indicates that the risk-adjusted individual demands depend on a term that is common to all agents and a term that is individual-specific. Since we are exploiting empirically the variation across agents, a linear approximation of (11) suggests the following econometric specification for agent i 's share of financial wealth invested in the stock market:

$$D_i = \%FW_i = \max\{0, \lambda_0 + \underset{(+)}{\lambda_1 k_i^*} + \underset{(+)}{\lambda_2 Expec R_i} + \underset{(-)}{\lambda_3 \rho_i} + \tau_i \lambda + u_i\}, \quad (20)$$

where u_i is an individual-specific error term. The vector τ_i contains individual characteristics for respondent i , like age, gender, marital status, number of children, geographical region of residence, employment status, assets, income, borrowing or liquid savings. As in our analysis of expectations and perceptions above, it also includes individual perceptions about the respondent's relative standing in terms of peer characteristics for both the respondent's social circle (professional status) and financial circle (professional status, education and total wealth),²⁷ as well as individual perceptions about population behavior/information. The signs under the constant coefficients indicate the theoretically predicted signs: more/better informed connections reduce the equilibrium posterior variance of expected returns and boost the desired risky portfolio share (coefficient λ_1); a higher expected net excess return (coefficient λ_2) and lower risk aversion (coefficient λ_3) similarly increase the desired fraction of financial wealth to be invested in the stock market, controlling for individual characteristics.

The zero term within the specification allows for the observed prevalence of non-stockholders in the population. The empirical literature on stockholding has dealt with stock market non-participation in two ways. One way is discrete choice estimation (typically probit and less frequently logit regressions) of the decision whether to hold stocks or not. Non-participation arises when the expected benefit from participation, which is a function of desired stockholding and the expected equity premium, does not exceed the participation cost. A second type of empirical approach invokes tobit estimation of the risky portfolio share. This is typically linked to the portfolio model by considering that an agent can have a desired portfolio share that is positive or negative, but the latter is restricted to zero through a constraint preventing short sales of stock. This offers a possibility to examine the household's degree of exposure to stockholding risk, as opposed to focusing only on its presence.²⁸ Note that, in both cases, portfolio demand, stock market expectations, and stock market perceptions play a potentially important role. By analogy to our analysis of expectations and perceptions above, we also

²⁷The detailed definitions of these can be found in Appendix B.

²⁸This standard approach should be interpreted with some caution, as it reduces stock market non-participants to frustrated short-sellers of stock. Nevertheless, it is consistent with the use of an estimator for censored data such as Tobit and opens up possibilities for studying the extensive margin.

consider another specification involving stockholding behavior among peers. This takes the form:

$$D_i = \%FW = \max\{0, \zeta_0 + \underset{(+)}{\zeta_1} D_i^e + \underset{(+)}{\zeta_2} Expec R_i + \underset{(-)}{\zeta_3} \rho_i + \tau_i \zeta + w_i\}, \quad (21)$$

where D_i^e represents the extent of peer participation in the stock market, as perceived by the respondent. In specification (20) we focus on respondents' perceptions about how informed their financial and outer circles are about the stock market; and in (21) we use their perceptions regarding the incidence of stock market participation in the two circles.

Stock Market Participation. Column (1) of Table 3 presents results for a standard stock market participation probit, which additionally employs responses on how informed the financial, the outer circle, and the population are perceived to be. We confirm that subjective expected returns are positively and significantly related to the probability of participation, consistent with existing portfolio models, even after controlling for a range of household characteristics and for the respondent's elicited absolute risk aversion. We find that a one standard deviation increase in the mean share of a respondent's financial circle that is informed about the stock market increases the probability of investing in stocks by 7.4 percentage points, representing about a 34% increase in the unconditional probability.

Column (2) repeats the exercise but now controls instead for respondent perceptions as to the prevalence of stock market participation in the two circles, as well as in the overall population. We find a statistically significant positive relationship with the perceived share of participating peers in the financial circle. This is consistent with either meaningful exchange of information with peers having first-hand familiarity with stockholding, or simply with mindful imitation of peers with whom the respondent has chosen to discuss financial matters.

However, our benchmark estimates also indicate that stock market participation among the outer circle has a positive and statistically significant relationship to the respondent's own decision to hold stocks, controlling for the perceived overall population participation rate, that turns out to be insignificant. This finding, together with the absence of an effect on expectations or perceptions, suggests the possible presence of mindless imitation of peers that the respondent does not consider knowledgeable or trustworthy enough to include in the financial circle. Indeed, in the absence of direct discussion of financial matters with the outer circle, respondent perceptions of participation in the stock market are likely to be based on casual remarks or inferences from other discussions and therefore to be much less precise. Although such imprecision could lead to insignificant estimates due to attenuation bias, we still find that those who do not hold inconsistent perceptions regarding their financial and overall social circle (and are therefore included in our benchmark sample) tend to relate their participation to perceived participation among their outer circle.²⁹ We will subject this finding to further scrutiny in the

²⁹Specifically, we find that a one-standard-deviation increase in the mean share of the respondent's financial circle investing in the stock market increases the probability to invest in stocks by around 6.3 percentage points, representing about a 30% increase relative to the sample mean proportion of stockholders of 21.7%; for the outer circle, the respective numbers are an increase in the probability to invest in stocks by 4 percentage points, representing a 19.5% increase relative to the sample mean proportion of stockholders.

robustness analysis below.

Conditional portfolio shares. Columns (5) and (6) of Table 3 adopt a tobit specification and report on the size of portfolio exposure to stockholding risk, conditional on holding stocks. Symmetrically to columns (1) and (2), columns (5) and (6) examine the role of perceptions regarding how informed the financial and outer circles are and to what extent they participate in the stock market, controlling also for perceptions about the population. Higher shares of informed or participating members of the financial circle are related to greater exposure to stockholding risk, conditional on participation, providing support for the main theoretical prediction.

It is noteworthy that the share of the outer circle investing in the stock market is also statistically significant for the conditional portfolio share, as it was for stock market participation, and it now accounts for about one half of the overall estimated peer effect on the share of wealth invested in the stock market.³⁰ We revisit this finding below.

All in all, our benchmark estimates provide consistent support for the view that informative interactions with the financial circle systematically influence the accuracy of return forecasts only through their influence on the accuracy of perceived past returns; and they influence conditional portfolio shares, as well as stock market participation, even beyond their effect through expected returns. The benchmark estimates provide indications of additional relevance of mindless imitation, to be examined further below.

We now turn to examining the robustness of these links between social interactions and perceptions, expectations, and actions to address various alternative interpretations.

6. ROBUSTNESS ANALYSIS

6.1. Endogenous formation of financial circle. Our baseline estimates condition on heterogeneous perceptions of peer circles at different levels, but do not allow explicitly for endogeneity of financial circle formation. The question of whether the share of informed or participating members of the financial circle contributes to errors or stockholding outcomes refers to those who have formed a financial circle. A potential concern is that unobserved factors might induce a respondent both to form a financial circle and to collect information so as to sharpen her forecast (backcast) of stock returns; or to decide on stock market participation and on the conditional risky portfolio share. To address this potential concern in the cases of accuracy of perceptions of past returns and of expectations for future returns, Table 4 reports estimates of Heckman regressions of absolute forecast or backcast errors, conditional on the respondent having chosen to form a financial circle.³¹ The first-stage regression estimates are

³⁰A one-standard-deviation increase in the mean share of the respondent's financial circle investing in the stock market is related to a higher conditional share of financial wealth invested in the stock market by around 1 percentage point, representing about a 4.3% increase relative to the sample mean share of 21.41% amongst stockholders. For the outer circle, the corresponding figure is a higher conditional share invested by 1.4 percentage points, representing a 6.4% increase relative to the sample mean.

³¹As a further robustness exercise, Table A9 in the online appendix reports estimates from seemingly unrelated regression (SUR) estimation, where the decision to form a financial circle and errors in perceptions or expectations are allowed to be arbitrarily related, with similar results.

reported in columns (a), while the second-stage (forecast or backcast) regressions appear in columns (b), for selected covariates.³² Table 2 shows that the key finding on absolute forecast errors, namely that social interaction variables play no role once backcast errors are controlled for, is robust to allowing for endogenous formation of the financial circle. Moreover, the null hypothesis of no correlation of unobserved factors in the decision to form a financial circle and in the absolute size of the forecast error cannot be rejected (see the reported statistics at the last two rows of Table 4). Estimates in columns 5(b) and 5(c) confirm the finding in Table 2 that the share of the financial circle perceived by the respondent to be informed about, or participating in stockholding is related to more accurate perceptions of the recent stock market realization, in the form of smaller absolute backcast errors. Thus our conclusion about information exchange or mindful imitation improving perceptions of the recent past return is robust to allowing for endogenous formation of the financial circle.

In a similar vein, respondents may have some unobserved reasons to hold stocks, or to choose higher stock exposure conditional on participation, that also encourage them to form a financial circle. We follow Blume et al. (2011) and we treat group choice and behavior (within a group) as a set of joint outcomes. Specifically, we consider a bivariate probit model for the choice to participate in the stock market and the choice to form a financial circle, allowing for correlated unobserved factors influencing the two choices.³³ We estimate the following bivariate probit specification:

$$\begin{cases} \Pr(FC_i > 0) = \Phi(\nu'_1 k_{iSC}^* + \nu'_2 k_{iPop}^* + \nu'_3 Expec R_i + \nu'_4 \rho_i + \tau_i \nu') \\ \Pr(Stocks_i > 0) = \Phi(\lambda_0 + \lambda_1 k_{iFC}^* + \lambda_2 k_{iOC}^* + \lambda_3 k_{iPop}^* + \lambda_4 Expec R_i + \lambda_5 \rho_i + \tau_i \lambda) \end{cases} \quad (22)$$

and the corresponding one for the perceived share of peers participating in stockholding, where we replace k^* with D^e . We are able to control for a number of observables that might influence the choice of a respondent to form a financial circle.

Table 5 presents four bivariate probits. Even-numbered columns depict the choice of whether to form a financial circle or not, while odd-numbered columns depict stock market participation. In addition to various demographic and economic characteristics of the respondent, we include regressors to capture the respondent's perception of how much is to be gained by forming a financial circle. Specifically, we include the respondent's perception as to the shares of the social circle that are informed about, or participating in, stocks, controlling for perceptions of the corresponding shares in the overall population; and perceptions of the share of the social circle that has higher or lower professional standing than the respondent. As can be seen in all (a) columns, perceiving a higher share of one's social circle as being informed about the stock market is significantly and positively correlated with the respondent's tendency to form a financial circle. The perceived share of stock market participants, in contrast, does not have any additional explanatory power, consistent with the view that information exchange is an

³²Table A3 in the online appendix reports the results for the full list of covariates.

³³An alternative approach in the literature is to instrument peer financial behavior; e.g. Brown, Ivkovic, Smith and Weisbenner (2008) use the one-year-lagged average equity ownership of nonnative community members' birth states for equity ownership within the community, when exploiting the variation across communities.

important motivation for having a financial circle. Elicited risk aversion, relevant for the likely usefulness of interactions with the financial circle, is negatively correlated to the likelihood of forming one.

Columns (b) refer to the second leg, of stock market participation. In all specifications, we find the tendency to participate in the stock market to be positively related to the subjective expected stock market return over the next five years. This provides a first channel through which social interactions enter stock market participation. A second is through the perceived share of the financial circle that is informed about, or participating in the stock market. This is also significantly and positively related to participation, consistent with the presence of information exchange and mindful imitation of peers considered knowledgeable and trustworthy enough to be included in the respondent's financial circle. Thus, our benchmark findings on stock market participation are also robust to allowing for endogenous financial circle formation.

Findings on the importance of the outer circle are mixed, as in our benchmark analysis. In column 1(b), we do not find a significant relationship with the share of the outer circle perceived as informed, while in column 2(b), we find evidence of a statistically significant and positive relationship of stock market participation to the respondent's perception regarding the share of the outer circle that participates in the stock market. This mirrors our finding in Table 3.

Thus, allowing for correlation among unobserved factors leading somebody to participate in stocks and to form a financial circle further supports our benchmark findings on the relevance of perceptions regarding financial circle information and participation in Table 3. The source of this robustness is highlighted in the last three rows of Table 5. The correlation under discussion is between the error terms u_i and v_{iFC} , in the form $u_i = \phi v_{iFC} + v_i$. The three rows report estimates of correlation ϕ , the Wald test statistics and associated p -values for different specifications of (22) considered. In no case can we reject the null of independence, $H_0 : \phi = 0$, between unobserved factors influencing the two choices.

6.2. Common preferences or shocks. An issue widely faced in the literature on peer effects is that of common preferences or common shocks. Applied to our case, individuals and their financial circles, with whom they discuss confidential financial matters, may be sharing common preferences in financial behavior or be affected similarly by exogenous shocks over time. These factors could be shifting both the proxy for peer effects and the outcome variable, thus inflating the estimated size of the peer effect. Specifically, they might induce a correlation between information collection or stock market participation in the financial circle and the accuracy of expectations and perceptions or the stockholding behavior of respondents that reflects, at least in part, the operation of common preferences or common reactions to shocks. If outer social circles are sufficiently less subject to common preferences and common shocks, the coefficient estimate on the outer circle may turn out to be insignificant, while the one on the financial circle shows up as significant.

A useful approach to testing for the presence of powerful underlying factors bringing about such patterns is to conduct placebo tests. The key peer variables are reshuffled among demo-

graphic groups relevant for financial circle formation and possibly facing common preferences or common shocks. If the coefficient estimates for the peer variables are no longer significant, this supports the conclusion that the benchmark estimates do not originate in a tendency of such groups to have common preferences or be faced by common shocks.

We have reshuffled responses regarding the financial and the outer circle, the population, as well as non-response dummies among respondents in the same age, education, and location group. As can be seen in Table 6, we no longer find that the shares of the financial circle perceived to be informed about, or participating in the stock market are significantly related to either absolute forecast or backcast errors of stock market returns. Those of the outer circle and of the population continue to be insignificant. This supports the view that our findings on the accuracy of stock return expectations and of perceptions regarding past performance do not arise from common preferences or shocks among people sharing age, education, and location.

A similar conclusion is reached when we push further and include even more characteristics that might be relevant for the formation of social circles and the experience of common preferences or shocks. In the online appendix Table A4, we reshuffle among respondents who share the same age, education, region of residence, marital status, occupational status, as well as having children. We find again that the coefficients on reshuffled peer variables turn insignificant. Thus, our findings cannot be attributed to common preferences or common shocks even using a much more granular social grouping.

Our results are consistent with recent work on a different dataset, which combines survey responses with administrative data from Vanguard in the US (Giglio, Maggiori, Stroebel, Utkus, 2020). The authors found that individual beliefs about future returns are not to be traced to demographic characteristics but mostly to heterogeneous and persistent individual fixed effects: some individuals are optimistic and others are pessimistic, and these differences are wide within groups sharing a number of demographic characteristics. Moreover, these beliefs are also not changing much over time in response to common shocks: in their panel estimation, the time variation in average expected returns accounts for only 2% of the total panel variation in expected returns, while 40-60% is accounted for by individual fixed effects.

Our supportive placebo results extend to our findings on stock market participation and on the conditional risky portfolio share, net of the peer effects on subjective expectations, for which we are controlling. Columns (3) and (4) of Table 3 report findings for reshuffling based on age, education, and region. The coefficients on reshuffled responses concerning the financial and the outer circle are not statistically significant for stock market participation, and the coefficients on the population perceptions remain insignificant. Columns (7) and (8) report our placebo findings for the intensive stockholding margin. Again, none of the reshuffled responses are significant. The findings reported in the online appendix Table A5 generalize these placebo results to allowing for the wider group of controlled characteristics described in the context of Table A4 above, confirming our findings.

An alternative approach to testing for the relevance of common preferences or common

shocks is to exploit an instrument that shifts the peer variable, but which itself has no direct effect on the outcome variable, except through its effect on the peer variable. One then examines if IV estimation renders the peer variable insignificant.³⁴ In our analysis, such an instrument should alter respondent perceptions about information or participation in their financial circle but should not directly influence the accuracy of respondent stock return forecasts, backcasts, and stockholding behavior. We have used as an instrument the respondent perception about the proportion of peers in the respondent’s financial circle who are homeowners. The primary residence is a real and much more observable asset than stocks, and respondents are likely to be exposed to it in the context of their broad social interactions, without any presumption that they discuss financial matters with their peers. As can be seen in Table A1 in the online appendix, this turns out to be a valid and predictive instrument, with all estimated coefficients on respective peer variables being multiples of those in the benchmark estimates reported in Tables 2 and 3. Statistical significance of the financial circle variable is lost only in the specification running the conditional risky portfolio share on the perceived share of the financial circle that is informed about the stock market. Nevertheless, we find no statistical evidence against the null of exogeneity, suggesting that the original formulation is preferred.³⁵

Finally, we ask respondents in four questions from the TNS2015 questionnaire (questions C5, D6, D7 and D8) 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 answer that less than half of their acquaintances are similar to them in terms of assets, qualifications and/or professional standing (Appendix B). In addition to this limited extent of homophily, as declared by the respondents, our empirical results are conditional on these social utility covariates, which are never statistically significant.

All in all, a combination of placebo tests, IV estimation, and self reports, consistent with recent results on return expectations in a different setup, suggest that our findings on the role of perceptions about peer stock market information or participation are not likely to be mere artifacts of common preferences or of responses to common shocks.

6.3. Attenuation Bias. Our findings on the importance of the outer circle were consistent between our benchmark estimates and those allowing for endogenous formation of the financial circle: perceptions about how informed the outer circle is turned out to be statistically insignificant, while those about the extent of participation in the outer circle were statistically significant. Now, a key difference between the financial circle and the outer social circle is that respondents do not purposefully discuss financial matters with the outer circle. An assessment of how informed the outer circle is would probably require considerable discussion of respondents with their outer circle peers, while an impression of participation could be based on casual or accidental remarks. As a result, respondents are likely to be more uncertain about their assessment of information in their outer circle than their assessment of participation. Is

³⁴A good recent example of this approach is Bailey et al. (2019), which uses Facebook data to assess peer effects in product adoption.

³⁵See Tables A1 and A2 in the online appendix.

the asymmetry in the estimates for perceived information and participation an indication of weak, if any, influence from the outer circle, or is it a mere manifestation of attenuation bias driving the coefficient on information in the outer circle towards zero? Although our emphasis is on the presence of informative social interactions with the financial circle, we take up this issue here.

Our benchmark sample already excludes respondents who give inconsistent answers regarding their financial and their overall social circle, so as to limit concerns about attenuation bias. Now we take the extra step of allowing respondent perceptions of their outer social circle to reflect, at least in part, their perceptions of overall population behavior. Specifically, We instrument responses on stock market information or participation in the outer circle with responses of the same individual regarding the respective share in the overall population (see Table 7, columns 1-4). These subjective responses on the population are quite consistent with existing population data on average and perform well in first-stage regressions.³⁶ We also control for a number of household characteristics, limiting the possibilities that perceptions regarding the population could be influencing stock market participation through omitted channels other than perceptions of the outer circle.

Odd-numbered columns in Table 7 report instrumental variable estimates for stock market participation (columns 1 and 3) and for the share of financial wealth conditional on participation (columns 5 and 7). Each of the nonlinear models, i.e. probits for stockholding and tobits for the conditional shares, is estimated jointly by maximum likelihood, under the null hypothesis of no measurement error. The Wald $\chi^2(1)$ reported at the bottom of Table 7 has associated p -values above 20% for all specifications, and thus we cannot reject the null of no measurement error.

The finding that the perceived degree of information in the outer circle is not systematically related to participation or the conditional portfolio share survives this further robustness exercise. If anything, Table 7 weakens further the case for the presence of mindless imitation, by showing insignificant coefficients on both outer circle variables, perceived information and participation. Importantly, the significance pattern of our benchmark estimates regarding the *financial* circle shares, i.e. informative social interactions, remains robust.

6.4. Reverse causality. A further possible concern is that our results on stock market participation reflect reverse causality: respondents who participate in stocks and those more exposed to stockholding risk in their portfolios may be more likely to convince themselves that their peers are also participating, possibly to justify their own choices.

It is hard to see, both a priori and in light of our overall findings, how reverse causality could lie behind our results. First, one could make the same "feel good about one's self" argument for

³⁶For the average stock market participation rate in our sample of 21.7%, respondents have on average a perception of 19.39% (see Table 8 of summary statistics). The results reported at the bottom of Table 7 under even-numbered columns show quantitatively big estimated effects and F-statistics above 40 for the first stage regressions of outer circle participation or information, as a function of population participation or information respectively.

perceptions regarding the population: those who hold stocks want to feel that they are not alone, not only in their financial circle but also more broadly. Yet, we find that respondent perceptions about the population tend to be quite accurate and not significantly related to precision of return expectations or perceptions, to stockholding behavior, or to perceptions about the financial circle. Second, we have found a robust positive relationship between perceptions of the financial circle and accuracy of perceptions regarding recent stock returns and of expectations about future performance. Thus, respondents who distort their perceptions of their financial circle tend to be more accurate in their perceptions of recent stock returns or in their forecasts of future returns. It is not obvious why greater accuracy in one dimension of perceptions should be related to, let alone cause, greater bias in another. Third, if respondents who are more precise in their return expectations or perceptions, or hold stocks or are more exposed to stock risk tend to distort their perceptions of participation in their financial circle in order to feel good about themselves, they could feel even better if they thought that the peers in whom they confide on financial matters are more informed. Yet, those with greater precision or experience with the stock market tend to be in a better position to judge how informed their peers are, stretching credibility further. Finally, instrumental variable estimation, reported in the online appendix, tends to find larger estimates of coefficients on the financial circle and fails to reject the null of exogeneity, suggesting that the non-instrumented results are to be preferred.³⁷

All in all, we find no reason to suspect that respondents who have more accurate perceptions, information, and experience with the market are also more likely to have artificially inflated perceptions of the degrees of information and participation among peers with whom they continually discuss financial matters.

7. CONCLUSIONS

We provide a model where purely informative social interactions influence subjective expectations of future stock market returns as well as the demand for investing in stocks, within a large efficient asset market. The model shows that, conditional on investing, individuals collect more information from better informed peers, and due to the improved precision that this generates, demand more stock in response to positive pooled signals. By designing, collecting, and exploiting novel survey data for a representative sample of the French population by age, wealth and asset classes, we find strong support for the presence of informative social interactions, but only mixed evidence for the presence of mindless imitation of perceived participation behavior in the outer social circle with whom respondents do not discuss finances.

Based on our findings, the extent to which respondents perceive the financial circle to be informed about, or participating in the stock market, tends to influence the accuracy of expectations of future returns by influencing the accuracy of perceptions of recent returns. Stock market participation and the degree of exposure to stocks, conditional on participation, are positively influenced by stock market expectations. However, this is not the only channel through

³⁷IV estimates for the extensive margin decision are reported in Table A6 in the online appendix, under columns (3) and (4), while those for the intensive margin are in columns (5) and (6). The corresponding first-stage regression estimates are in Table A7 in the online appendix, under the respective column numbers.

which peers influence stockholding behavior. Even controlling for subjective expectations, stock market participation and the conditional portfolio share are additionally positively influenced by the extent to which the financial circle is informed or participating, both of which reduce the posterior variance of expected returns. These findings are consistent with the notion that social interactions tend to be informative in relation to stockholding at various levels, ranging from perceptions of the past to the degree of risk exposure. We have found our results to be robust to a number of possible alternative interpretations: endogenous formation of the financial circle, common preferences or shocks, attenuation bias, and reverse causality.

The presence of informative social interactions permeating different levels imply a potentially powerful channel through which financial information, financial literacy and financial knowledge can spread through the economy, even if the original content reaches a relatively small segment of the population. We found evidence for this social multiplier even in a country with advanced financial development and in products that are mature and widely known, as is the case of stocks. They could provide at least a partial substitute for financial advice, when the latter is ill-conceived, poorly incentivized, or hardly trusted. Finally, they are likely to grow in importance, as use of social media and the potential to reach more people with new information spread rapidly. Yet, the inequities involved in having access to less informed or less financially experienced peers point to potential distributional consequences and suggest caution in relying exclusively on informative social interactions for the spread of useful information and best financial practices.

REFERENCES

- [1] Afrouzi, H., O. Coibion, Y. Gorodnichenko and S. Kumar, 2016. Inflation Targeting Does Not Anchor Inflation Expectations: Evidence from Firms in New Zealand, *Brookings Papers on Economic Activity* 2015: 151–225.
- [2] Armantier, O., Nelson, S., Topa, G., Van Der Klaauw, W. and Zafar, B., 2016. The Price is Right: Updating Inflation Expectations in a Randomized Price Information Experiment. *The Review of Economics and Statistics*.
- [3] Arrondel, L., Calvo-Pardo, H., and D. Tas, 2014. Subjective Return Expectations, Information and Stock Market Participation: Evidence from France. Southampton Discussion Paper Series in Economics and Econometrics.
- [4] Biliias, Y., D. Georgarakos and M. Haliassos, 2010. Portfolio Inertia and Stock Market Fluctuations. *Journal of Money, Credit, and Banking* 42(4): 715–742.
- [5] Bailey, M., R. Cao, T. Kuchler and J. Stroebel, 2016. Social Networks and Housing Markets, NBER WP 22258.
- [6] Bailey, M., D. Johnston, T. Kuchler, J. Stroebel, A. Wong, 2019. Peer Effects in Product Adoption, NBER WP 25843.

- [7] Banerjee, A., A.G. Chandrasekhar, E. Duflo and M. Jackson, 2013. The Diffusion of Microfinance. *Science* 341, 1236498.
- [8] Beshears, J., J. J. Choi, D. Laibson, B. C. Madrian and K. L. Milkman, 2015. The effect of providing peer information on retirement savings decisions, *Journal of Finance*, 70:1161–1201.
- [9] Blume, L. E., W. A. Brock, S. N. Durlauf and Y. M. Ioannides, 2011. Identification of Social Interactions. In Jess Benhabib, M. Jackson and A. Bisin eds., *Handbook of Social Economics*, Vol. 1B, ch. 18, North-Holland.
- [10] Bordalo, P., N. Gennaioli, R. LaPorta, and A. Shleifer, 2019. “Diagnostic Expectations and Stock Returns.” *Journal of Finance* forthcoming.
- [11] Brandt, M. W., 2010. Portfolio Choice Problems. In Y. Ait-Sahalia and L.P. Hansen, eds., *Handbook of Financial Econometrics*, Elsevier Science: Amsterdam.
- [12] Brown, J. R., Z. Ivkovic, P. A. Smith and S. Weisbenner, 2008. Neighbors Matter: Causal Community Effects and Stock Market Participation. *The Journal of Finance* 63(3): 1509–1531.
- [13] Burnside, C., M. Eichenbaum, and S. Rebelo, 2016. Understanding Booms and Busts in Housing Markets. *Journal of Political Economy* 124(4): 1088-1147.
- [14] Burszty, L., F. Ederer, B. Ferman, and N. Yuchtman, 2014. Understanding Mechanisms underlying Peer Effects: Evidence from a Field Experiment on Financial Decisions. *Econometrica* 82(4): 1273–1301.
- [15] Cabrales, A., O. Gossner, and R. Serrano. 2013. Entropy and the Value of Information for Investors. *American Economic Review*, 103(1): 360–377.
- [16] Cabrales, A., O. Gossner, and R. Serrano. 2017. A Normalized Value for Information Purchases. *Journal of Economic Theory*, 170: 266–288.
- [17] Campbell, J. Y., 2016. Restoring Rational Choice: The Challenge of Consumer Financial Regulation. *American Economic Review: Papers & Proceedings*, 106(5): 1–30.
- [18] Carroll, C. D., 2003. Macroeconomic Expectations of Households and Professional Forecasters. *Quarterly Journal of Economics* 118(1):269–298.
- [19] Christelis, D., T. Jappelli and M. Padula, 2010. Cognitive Abilities and Portfolio Choice. *European Economic Review* 54: 18–38.
- [20] Coibion, O., Y. Gorodnichenko and S. Kumar, 2018. How Do Firms Form Their Expectations? New Survey Evidence. *American Economic Review*, 108(9): 2671–2713.

- [21] De Paula, A., 2010. Econometrics of Network Models. Cemmap working paper, Centre for Microdata Methods and Practice, No. CWP06/16.
- [22] Dimmock, S. G., R. Kouwenberg, O. S. Mitchell and K. Peijnenburg, 2016. Ambiguity aversion and household portfolio choice puzzles: Empirical evidence. *Journal of Financial Economics*, 119(3), pp. 559–577.
- [23] Dimson E., P. Marsh and M. Staunton, 2008. Worldwide equity premium: a smaller puzzle. Ch. 11 in R. Mehra ed., *Handbook of the equity risk premium*, Elsevier, pp. 467–514.
- [24] Dominitz, J. and C. Manski, 2007. Expected Equity Returns and Portfolio Choice: Evidence from the Health and Retirement Study. *Journal of the European Economic Association* 5: 369–79.
- [25] Duflo, E. and E. Saez, 2002. Participation and investment decisions in a retirement plan: the influence of colleagues’ choices, *Journal of Public Economics* 85: 121–148.
- [26] Duflo, E. and E. Saez, 2003. The Role of Information and Social Interactions in Retirement Plan Decisions: Evidence from a Randomized Experiment, *Quarterly Journal of Economics* 118(3): 815–842.
- [27] Easley, D., M. O’Hara and L. Yang, 2016. Differential Access to Price Information in Financial Markets. *Journal of Financial and Quantitative Analysis*, 51(4): 1071–1110.
- [28] Georgarakos, D., M. Haliassos, and G. Pasini, 2014. Household Debt and Social Interactions, *Review of Financial Studies*, 27(5), 1404–1433.
- [29] Giglio, S., M. Maggiori, J. Stroebe, S. Utkus, 2020. Five Facts About Beliefs and Portfolios, *Mimeograph*.
- [30] Girshina, A., T.Y. Mathae and M. Ziegelmeyer, 2019. Peer effects in stock market participation: Evidence from immigration, *Mimeograph*.
- [31] Gomes, F., M. Haliassos and T. Ramadorai, 2020. Household Finance, forthcoming in the *Journal of Economic Literature*.
- [32] Greenwood, R. and A. Schleifer, 2014. Expectations of Returns and Expected Returns, *Review of Financial Studies*, 27(3): 714–746.
- [33] Gourieroux, C., A. Monfort, E. Renault and A. Trognon, 1987. Generalized residuals, *Journal of Econometrics*, 34(1–2), 5–32.
- [34] Grinblatt, M., M. Keloharju, and S. Ikäheimo, 2008. Social Influence and Consumption: Evidence from the Automobile Purchases of Neighbors. *The Review of Economics and Statistics*, 90(4): 735–753.

- [35] Guiso, L. and T. Jappelli, 2005. Awareness and Stock Market Participation. *Review of Finance*, 9: 537–567.
- [36] Guiso, L., T. Jappelli and D. Terlizzese, 1996. Income risk, borrowing constraints and portfolio choice. *American Economic Review*, 86: 158–172.
- [37] Guiso, L. and M. Paiella, 2008. Risk Aversion, Wealth and Background Risk, *Journal of the European Economic Association*, 6(6), 1109–1150.
- [38] Haliassos, M, T. Jansson and Y. Karabulut, 2020. Financial Literacy Externalities, *Review of Financial Studies*, . 33(2), 950–989.
- [39] Hong, H., Kubik, J.D., and J.C. Stein, 2004. Social interaction and stock market participation. *The Journal of Finance*, 59: 137–163.
- [40] Hurd, M. D., 2009. Subjective Probabilities in Household Surveys. *Annual Review of Economics*, 1: 543–562.
- [41] Hurd, M. D., M. Van Rooij and J. Winter, 2011. Stock Market Expectations of Dutch Households. *Journal of Applied Econometrics* 26(3): 416-436.
- [42] Jackson, M., 2008. Social and Economic Networks. Princeton University Press.
- [43] Jonung, L., 1981. Perceived and Expected rates of Inflation in Sweden. *American Economic Review*, 71(5): 961-68.
- [44] Kaustia M. and S. Knüpfer, 2012. Peer performance and stock market entry, *Journal of Financial Economics* 104(2): 227–420.
- [45] Kézdi, G. and R. J. Willis, 2009. Stock Market Expectations and Portfolio Choice of American Households. Mimeograph.
- [46] Le Bris, D. and P.-C. Hautcoeur, 2010. A challenge to triumphant optimists? A blue chips index for the Paris stock exchange, 1854–2007. *Financial History Review*, 17:141–183.
- [47] Li, J. and L. Lee, 2009. Binary Choice under Social Interactions: An Empirical Study with and without Subjective data on Expectations. *Journal of Applied Econometrics*, 140: 333–374.
- [48] Lusardi, A. M., P.-C. Michaud and O. Mitchell, 2016. Optimal Financial Knowledge and Wealth Inequality. *Journal of Political Economy* 125(2): 431–477.
- [49] Lusardi, A. M., and O. S. Mitchell, 2014. The Economic Importance of Financial Literacy: Theory and Evidence. *Journal of Economic Literature*, 52(1): 5–44.
- [50] Manski, C., 1993. Identification of Endogenous Social Effects: The Reflection Problem. *The Review of Economic Studies*, 60(3): 531-542.

- [51] Manski, C., 2004. Measuring Expectations. *Econometrica*, 72: 1329–76.
- [52] Manski, C., 2017. Survey Measurement of Probabilistic Macroeconomic Expectations: Progress and Promise, *NBER Macroeconomics Annual* Vol. 32, *forthcoming*.
- [53] Ouimet, P. and G. Tate, 2017. Learning from coworkers: Peer effects on individual investment decisions. *NBER* WP24058.
- [54] Ozsoylev, H. N. and J. Walden, 2011. Asset pricing in large information networks. *Journal of Economic Theory* 146, 2252–2280.
- [55] Peress, J., 2004. Wealth, Information Acquisition and Portfolio Choice. *Review of Financial Studies* 17(3): 879–914.
- [56] Sims, C., 2003. Implications of Rational Inattention. *Journal of Monetary Economics* 50(3): 665–690.
- [57] Van Nieuwerburgh, S. and L. Veldkamp, 2010. Information Acquisition and Under-Diversification. *Review of Economic Studies*, 77(2): 779–805.

TABLE 1: Abbreviations and notation

Abbreviation	Stands for	Questions	From
SC	Social circle	C1	TNS2015
FC	Financial circle	D1	TNS2015
OC	Outer circle	C1, D1	TNS2015
%SC Inform.	Perceived share of SC members informed about stock market	C7ii	TNS2015
%SC Particip.	Perceived share of SC members investing the stock market	C7i	TNS2015
%FC Inform.	Perceived share of FC members informed about stock market	D16ii	TNS2015
%FC Particip.	Perceived share of SC members investing in stock market	D16i	TNS2015
%OC Inform.	Perceived share of OC members informed about stock market	C1, D1, C7ii/D16ii	TNS2015
%OC Particip.	Perceived share of OC members investing in stock market	C1, D1, C7i/D16i	TNS2015
% Pop. Inform.	Perceived proportion of the French population informed about stock market	C6ii	TNS2015
%Pop. Particip.	Perceived proportion of the French population investing in stock market	C6i	TNS2015
SC Rel.Stand. Prof.+	Perceived share of SC members performing better professionally	C5a	TNS2015
SC Rel.Stand. Prof.-	Perceived share of SC members performing worse professionally	C5c	TNS2015
FC Rel.Stand. Prof.+	Perceived share of FC members performing better professionally	D6a	TNS2015
FC Rel.Stand. Prof.-	Perceived share of FC members performing worse professionally	D6c	TNS2015
FC Rel.Stand. Wealth+	Perceived share of FC members with higher wealth	D7	TNS2015
SC Rel.Stand. Edu.+	Perceived share of SC members with higher educational attainment	D8	TNS2015
%FW	Share of financial wealth invested in the stock market	C19	TNS2014
Pr(stocks >0)	Probability of holding stocks (directly and/or indirectly)	C19, C3	TNS2014
Perc. R	Perceived mean realized stock market returns	C42	TNS2014
Expec. R	Subjective mean expected stock market returns	C39	TNS2014

TABLE 2: Forecast and Back/Nowcast errors (short)

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	$ FER $	$ FER $	$ FER $	$ FER $	$ FER $	$ BER $	$ BER $
%FC. Inf.	-0.0263** (0.0131)			-0.0129 (0.0129)		-0.0513*** (0.0193)	
%OC. Inf.	-0.0005 (0.0259)			0.00218 (0.0239)		-0.0148 (0.0370)	
%Pop. Inf.	0.0118 (0.0166)		0.0123 (0.0184)	0.0104 (0.0159)		-0.00140 (0.0224)	
%FC. Part.		-0.0247** (0.0124)			-0.0126 (0.0120)		-0.0452** (0.0200)
%OC. Part.		0.0003 (0.0335)			0.0089 (0.0323)		-0.0455 (0.0439)
%Pop. Part.		0.0068 (0.0209)	-0.0049 (0.0237)		0.0037 (0.0195)		0.0026 (0.0255)
SC Rel.Stand. Prof.+	-0.0089 (0.0132)	-0.0085 (0.0132)	-0.0016 (0.0119)	-0.0027 (0.0118)	-0.0030 (0.0118)	-0.0231 (0.0198)	-0.0208 (0.0196)
SC Rel.Stand. Prof -	-0.0230 (0.0146)	-0.0233 (0.0148)	-0.0204 (0.0139)	-0.0188 (0.0135)	-0.0194 (0.0136)	-0.0222 (0.0229)	-0.0198 (0.0228)
FC Rel.Stand. Prof.+	0.0103 (0.0114)	0.0098 (0.0115)	0.0135 (0.0109)	0.0142 (0.0107)	0.0129 (0.0107)	-0.0207 (0.0183)	-0.0185 (0.0185)
FC Rel.Stand. Prof.-	-0.0020 (0.0139)	-0.0023 (0.0139)	0.0084 (0.0136)	0.0056 (0.0132)	0.0054 (0.0132)	-0.0330 (0.0209)	-0.0336 (0.0206)
FC Rel.Stand. Weal.+	-0.3550 (0.3360)	-0.3850 (0.3380)	-0.3370 (0.3070)	-0.3680 (0.3070)	-0.3940 (0.3100)	0.0196 (0.4750)	-0.0111 (0.4750)
FC Rel.Stand. Educ.+	-4.14e-05 (0.3210)	-0.00172 (0.3200)	-0.0152 (0.3060)	-0.0172 (0.3060)	-0.0246 (0.3050)	0.1230 (0.4690)	0.1480 (0.4650)
$ BER $			0.271*** (0.0230)	0.271*** (0.0230)	0.272*** (0.0230)		
Risk aversion	0.0686* (0.0380)	0.0699* (0.0380)	0.0405 (0.0342)	0.0386 (0.0341)	0.0387 (0.0341)	0.145*** (0.0525)	0.150*** (0.0525)
Socio-demo characteristics: ^a	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Socio-econ characteristics: ^b	Yes	Yes	Yes	Yes	Yes	Yes	Yes
NR, DK, IC indicators: ^c	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,535	2,535	2,535	2,535	2,535	2,328	2,328
F	2.544	2.599	4.971	4.846	4.841	4.331	4.345
R^2	0.054	0.054	0.162	0.164	0.165	0.097	0.096

Notes: The table reports Huber-robust regressions of households' absolute forecast errors $|FER| \equiv |R_{t+1} - F^i R_{t+1}|$ (columns 1-5) and back/nowcast errors $|BER| \equiv |R_t - B^i R_t|$ (columns 6-7), for stock market returns on the CAC-40 index over the next five or and last three years respectively, on our measures of informative social interactions. Columns 3-5 report results for households' absolute forecast errors conditional on back/nowcast errors. (^a) Age, gender, marital status and children at home. (^b) Education (college or more), region of residence, employment status, total wealth, income and savings distribution quartiles and borrowing/liquidity constrained status. (^c) The full set of Non-response (NR), Does-not-Know (DK) and Inconsistent (IC) categories is as specified in Table 8. Reference categories are: 18-34 year old, Female, less than college education, single, widow or divorced, out of the labor force, region 1 (living in Paris), borrowing and liquidity unconstrained, and the first quartiles of the total wealth, income and savings distribution, respectively. Robust standard errors are reported in parentheses. ***, ** and * denote significance at 1%, 5% and 10%, respectively. Source: merged TNS2014 and TNS2015 waves in France.

TABLE 3: Stockholdings

VARIABLES	(1) Pr(Stocks >0)	(2) Pr(Stocks >0)	(3) Pr(Stocks >0) Placebo	(4) Pr(Stocks >0) Placebo	(5) E(%FW >0)	(6) E(%FW >0)	(7) E(%FW >0) Placebo	(8) E(%FW >0) Placebo
%FC Inform.	0.0027*** (0.0005)		-0.0003 (0.0006)		0.0290 (0.0198)		0.0259 (0.0208)	
%OC Inform.	0.0001 (0.0013)		0.0024 (0.0013)		0.0415 (0.0416)		-0.0643 (0.0419)	
%Pop. Inform.	-0.0006 (0.0008)		8.71e-0.5 (0.0008)		-0.0392 (0.0308)		0.0360 (0.0261)	
%FC Particip.		0.0021*** (0.0006)		-0.0002 (0.0007)		0.0326* (0.0190)		0.0155 (0.0208)
%OC Particip.		0.0024* (0.0012)		0.0011 (0.0014)		0.0799** (0.0397)		-0.0329 (0.0437)
%Pop. Particip.		-0.0002 (0.0009)		0.0005 (0.0009)		-0.0229 (0.0362)		0.0170 (0.0293)
SC Rel.Stand. Prof.+	7.88e-05 (0.0007)	-5.59e-05 (0.0006)	-0.0002 (0.0007)	0.0001 (0.0007)	-0.0157 (0.0265)	-0.0173 (0.0274)	-0.0155 (0.0230)	-0.0156 (0.0225)
SC Rel.Stand. Prof.-	-0.0001 (0.0007)	0.0001 (0.0007)	0.0003 (0.0007)	0.0004 (0.0007)	0.0026 (0.0244)	0.0095 (0.0258)	0.02840 (0.0239)	0.0262 (0.023)
FC Rel.Stand. Prof.+	0.0002 (0.0065)	0.0002 (0.0006)	0.0009 (0.0006)	0.0006 (0.0006)	0.0081 (0.0232)	0.00290 (0.0238)	0.0166 (0.0195)	0.0171 (0.0191)
FC Rel.Stand. Prof.-	0.0001 (0.0008)	0.0002 (0.0008)	-0.0004 (0.0008)	-0.0003 (0.0008)	-0.0191 (0.0254)	-0.0208 (0.0269)	-0.0373 (0.0244)	-0.0359 (0.0240)
FC Rel.Stand. Wealth+	-0.0014 (0.0190)	0.0002 (0.0184)	-0.0015 (0.0181)	-0.0017 (0.0178)	0.3440 (0.617)	0.4020 (0.6450)	0.1260 (0.5600)	0.1150 (0.5470)
FC Rel.Stand. Edu.+	0.0054 (0.0187)	0.0062 (0.0183)	0.0095 (0.0179)	0.0096 (0.0177)	0.7610 (0.6450)	0.7790 (0.6740)	0.9310* (0.5620)	0.9100* (0.5480)
Expec. R	0.0021** (0.0009)	0.0021** (0.0009)	0.0020** (0.0010)	0.0020** (0.0009)	0.1070*** (0.0351)	0.1100*** (0.0366)	0.0820** (0.0325)	0.0800*** (0.0318)
Risk aversion	-0.0042** (0.0018)	-0.0040** (0.0018)	-0.0038** (0.0017)	-0.0038** (0.0017)	-0.1120* (0.0607)	-0.1120* (0.0630)	-0.0957* (0.0536)	-0.0973* (0.0523)
Socio-demographic characteristics: ^a	yes	yes	yes	yes	yes	yes	yes	yes
Socio-economic characteristics: ^b	yes	yes	yes	yes	yes	yes	yes	yes
NR, DK, IC indicators: ^c	yes	yes	yes	yes	yes	yes	yes	yes
Observations	2,525	2,525	2,506	2,506	2,294	2,294	2,277	2,277
Log-likelihood	-1190	-1192	-1145	-1146	-3618	-3615	-3395	-3396
LR χ^2	445.1	446.0	430.5	426.9	408.9	413.3	349.1	445.7
Pseudo R ²	0.1770	0.1750	0.1580	0.1570	0.0535	0.0541	0.0489	0.0484

Notes: Marginal effects from probits of stock market participation (cols. 1-4) and tobits of share of financial wealth invested in the stock market (direct or indirect), conditional on investing (cols. 5-8), on share of FC and OC circles informed about or participating in the stock market. ^(a) Age, gender, marital status and children at home. ^(b) Education (college or more), region of residence, employment status, total wealth, income and savings distribution quartiles and borrowing/liquidity constrained status. ^(c) The set of Non-response (NR), Does-not-Know (DK) and Inconsistent (IC) categories is as specified in Table 8. Reference categories are as in Table 2a. Robust standard errors are reported in parentheses. ***, ** and * denote significance at 1%, 5% and 10%, respectively. Source: merged TNS2014 and TNS2015 waves.

TABLE 4: Forecast and Back/Nowcast errors, conditional on having a Financial Circle (FC) (short)

VARIABLES	(1a) Pr(FC >0)	(1b) FE R	(2a) Pr(FC >0)	(2b) FE R	(3a) Pr(FC >0)	(3b) FE R	(4a) Pr(FC >0)	(4b) FE R	(5a) Pr(FC >0)	(5b) BE R	(6a) Pr(FC >0)	(6b) BE R
% SC Inf.	0.0104** (0.0052)		0.0087 (0.0056)		0.0103* (0.0053)		0.0093* (0.0055)		0.0096* (0.0052)		0.0091 (0.0817)	
%FC Inf.		-0.0227* (0.0127)		-0.0065 (0.0131)						-0.0572*** (0.0175)		
%OC. Inf.		-0.0167 (0.0251)		-0.0035 (0.0260)						-0.0758** (0.0386)		
% SC Part.	-0.0001 (0.0052)		0.0005 (0.0061)		-0.0002 (0.0053)		-0.0002 (0.0057)		-0.0006 (0.0052)		-0.0003 (0.0394)	
%FC. Part.						-0.0180 (0.0118)		-0.0063 (0.0128)				-0.0507** (0.0254)
%OC. Part.						-0.0183 (0.0323)		0.0024 (0.0365)				-0.0858 (0.4040)
%Pop. Inf.	-0.0054 (0.0038)	-0.0234 (0.0215)	-0.0059 (0.0039)	-0.0186 (0.0224)	-0.0057 (0.0037)		-0.0065* (0.0038)		-0.0049 (0.0038)	0.0102 (0.0311)	-0.0046 (0.0420)	
%Pop. Part.	-0.0004 (0.0044)		-0.0006 (0.0045)		-3.64e-06 (0.0043)	-0.0288 (0.0275)	0.0002 (0.0044)	-0.0262 (0.0273)	-0.0009 (0.0042)		-0.0011 (0.0408)	0.0017 (0.334)
SC Rel.Stand.Prof.+	0.0026 (0.0022)	-0.0099 (0.0171)	0.0026 (0.0022)	-0.0157 (0.0178)	0.0026 (0.0022)	-0.0086 (0.0165)	0.0026 (0.0022)	-0.0175 (0.0172)	0.0021 (0.0021)	0.0089 (0.0247)	0.0021 (0.0022)	0.0129 (0.2560)
SC Rel.Stand.Prof -	0.0024 (0.0025)	-0.0471*** (0.0181)	0.0022 (0.0025)	-0.0544*** (0.0184)	0.00241 (0.0025)	-0.0462** (0.0180)	0.0022 (0.0025)	-0.0582*** (0.0179)	0.0025 (0.0025)	0.00740 (0.0266)	0.0025 (0.0026)	0.0180 (0.2030)
FC Rel.Stand.vars: ^a BE R	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
				0.2870*** (0.0362)				0.2890*** (0.0368)				
Risk aversion	-0.0175** (0.0081)	0.0380 (0.0553)	-0.0154* (0.0084)	0.0501 (0.0607)	-0.0176** (0.0082)	0.0428 (0.0553)	-0.0155* (0.0084)	0.0464 (0.0580)	-0.0167** (0.0079)	0.0965 (0.0844)	-0.0168 (0.0114)	0.103 (1.230)
Socio-demo inc.: ^b	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Socio-econ inc.: ^c	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
NR/DK/IC cat. inc.: ^d	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
ϕ		-0.181		-0.322		-0.115		-0.219		-0.172		-0.118
$\chi^2, H_0:\phi=0$ (p-value)		0.22 (0.6390)		0.81 (0.3693)		0.16 (0.6868)		0.61 (0.4349)		0.40 (0.686)		0.00 (0.9944)
Observations		2021		1920		2021		1920		1966		1966

Notes: The table reports Huber-robust Heckman regressions of absolute forecast (cols. 1-4), $|FE R| \equiv |R_{t+1} - F^i R_{t+1}|$, and back/nowcast errors (cols. 5-6), $|BE R| \equiv |R_t - B^i R_t|$, for returns on the CAC-40 over the next five and last three years respectively: columns labeled (a) report results of the probit selection equation for having a financial circle and columns labeled (b) report results of Huber-robust regressions of forecast and back/nowcast errors, conditional on having a financial circle. Equations are jointly estimated by ML. A constant is included, but not reported. Controls include ‘non response’ (NR), ‘do not know’ (DK) and ‘inconsistent’ (IC) categorical variables (not reported here but in Table 8). The penultimate line reports a Wald test of independent equations (and associated p-values) under the null of no correlation $\phi = 0$ between having a financial circle and the absolute forecast back/nowcast error for stock market returns. The third line from the end reports the estimated correlation between the errors of both equations. (^a) FC Rel. Stand. +Profes., +Wealth and +Edu. (^b) Age, gender, marital status and children at home. (^c) Education (college or more), region of residence, employment status, total wealth, income and savings distribution quartiles and borrowing/liquidity constrained status. (^d). Reference categories are as in Table 2. Robust standard errors reported in parentheses. ***, ** and * denote significance at 1%, 5% and 10%, respectively. Source: merged TNS2014 and TNS2015 waves.

TABLE 5: Bivariate probits

VARIABLES	(1a) Pr(FC >0)	(1b) Pr(Stocks >0)	(2a) Pr(FC >0)	(2b) Pr(Stocks >0)	(3a) Pr(FC >0)	(3b) Pr(Stocks >0)	(4a) Pr(FC >0)	(4b) Pr(Stocks >0)
%FC Inform.		0.0026*** (0.0006)				0.0025*** (0.0005)		
%OC Inform.		0.0003 (0.0013)						
%SC Inform.	0.0034** (0.0015)		0.0033** (0.0014)		0.0034** (0.0015)		0.0033** (0.0014)	
%Pop. Inform.	-0.0014 (0.0011)	-0.0004 (0.0008)	-0.0014 (0.0011)		-0.0014 (0.0011)	-0.0004 (0.0008)	-0.0014 (0.0011)	
%FC Particip.				0.0022*** (0.0006)				0.0027*** (0.0006)
%OC Particip.				0.0026** (0.0012)				
%SC Particip.	-0.0007 (0.0015)		-0.0006 (0.0014)		-0.0007 (0.0015)		-0.0007 (0.0015)	
%Pop. Particip.	-0.0001 (0.0013)		-0.0001 (0.0012)	-0.0002 (0.0009)	-0.0001 (0.0013)		-0.0001 (0.0012)	0.0001 (0.0009)
SC Rel.Stand. Prof.+	0.0001 (0.0006)	-0.0003 (0.0007)	0.0001 (0.0006)	-0.0004 (0.0007)	0.0001 (0.0006)	-0.0004 (0.0007)	0.0001 (0.0006)	-0.0004 (0.0007)
SC Rel.Stand. Prof.-	0.0006 (0.0007)	-0.0002 (0.0007)	0.0006 (0.0007)	9.29e-05 (0.0007)	0.0006 (0.0007)	-0.0002 (0.0007)	0.0006 (0.0007)	-6.11e-05 (0.0007)
FC Rel.Stand.vars. inc.: ^a Expec.R	no 0.0003 (0.0011)	yes 0.0024** (0.0012)	no 0.0003 (0.0010)	yes 0.0023** (0.0011)	no 0.0003 (0.0011)	yes 0.0025** (0.0012)	no 0.0003 (0.0011)	yes 0.0024** (0.0012)
Risk Aversion	-0.0042* (0.0024)	-0.0041* (0.0023)	-0.0042* (0.0023)	-0.0039* (0.0022)	-0.0042* (0.0024)	-0.0043* (0.0023)	-0.0042* (0.0024)	-0.0040* (0.0023)
Socio-demogr. inc.: ^b	yes	yes	yes	yes	yes	yes	yes	yes
Socio-econ. inc.: ^c	yes	yes	yes	yes	yes	yes	yes	yes
NR/DK/IC cat. inc.: ^d	yes	yes	yes	yes	yes	yes	yes	yes
Observations	1,684		1,684		1,684		1,684	
Log-likelihood	-1789		-1790		-1791		-1793	
LR χ^2 (p-value)	637.6 (0)		640.6 (0)		629.2 (0)		622.8 (0)	
ϕ	0.0346		0.0415		0.0422		0.0440	
Wald χ^2 , $H_0:\phi=0$ (p-value)	0.420 (0.517)		0.612 (0.434)		0.633 (0.426)		0.694 (0.405)	

Notes: Marginal effects from bivariate probits of (i) formation of financial circle (columns labeled a). and (ii) stock market participation (columns labeled b). (^a) FC Rel. Stand. +Profes., +Wealth and +Edu. (^b) Age, gender, marital status and children at home. (^c) Education (college or more), region of residence, employment status, total wealth, income and savings distribution quartiles and borrowing/liquidity constrained status. (^d). Reference categories are as in Table 2. Robust standard errors are reported in parentheses. ***, ** and * denote significance at 1%, 5% and 10%, respectively. Source: merged TNS2014 and TNS2015 waves.

TABLE 6: Forecast and Back/Nowcast errors, placebo regressions

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
	$ FER $ Placebo	$ FER $ Placebo	$ FER $ Placebo	$ FER $ Placebo	$ BER $ Placebo	$ BER $ Placebo
%FC. Inf.	0.0096 (0.0142)		0.0123 (0.0131)		-0.0042 (0.0207)	
%OC. Inf.	0.0046 (0.0247)		-0.0039 (0.0251)		0.0515 (0.0368)	
%Pop. Inf.	-0.0072 (0.0149)		0.0190 (0.0162)		0.0230 (0.0256)	
%FC. Part.		0.0167 (0.0155)		0.0126 (0.0144)		-0.0011 (0.0206)
%OC. Part.		-0.0086 (0.0347)		-0.0270 (0.0343)		0.0236 (0.0440)
%Pop. Part.		-0.0216 (0.0171)		-0.0284 (0.0185)		0.0068 (0.0290)
SC Rel.Stand. Prof.+	-0.0068 (0.0134)	-0.0077 (0.0134)	-0.00273 (0.0128)	-0.0032 (0.0127)	-0.0226 (0.0197)	-0.0250 (0.0196)
SC Rel.Stand. Prof -	-0.0244 (0.0149)	-0.0256* (0.0150)	-0.0237 (0.0148)	-0.0243 (0.0149)	-0.0226 (0.0231)	-0.0232 (0.0232)
FC Rel.Stand. Prof.+	0.0046 (0.0117)	0.0052 (0.0117)	0.0088 (0.0112)	0.0093 (0.0113)	-0.0287 (0.0186)	-0.0273 (0.0187)
FC Rel.Stand. Prof.-	0.0002 (0.0142)	0.0018 (0.0142)	0.0068 (0.0141)	0.0078 (0.0142)	-0.0262 (0.0211)	-0.0258 (0.0211)
FC Rel.Stand. Weal.+	-0.3150 (0.3390)	-0.2950 (0.3380)	-0.3070 (0.3160)	-0.3180 (0.3170)	-0.0221 (0.478)	-0.0359 (0.4800)
FC Rel.Stand. Educ.+	-0.0193 (0.3250)	-0.0048 (0.3240)	-0.0109 (0.3280)	0.0432 (0.3270)	0.112 (0.4740)	0.1260 (0.4740)
$ BER $			0.274*** (0.0228)	0.275*** (0.0228)		
Risk aversion	0.0632 (0.0387)	0.0639* (0.0385)	0.0551 (0.0392)	0.0538 (0.0390)	0.151*** (0.0531)	0.155*** (0.0530)
Socio-demographic characteristics: ^a	Yes	Yes	Yes	Yes	Yes	Yes
Socio-economic characteristics: ^b	Yes	Yes	Yes	Yes	Yes	Yes
NR, DK, IC indicators: ^c	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,516	2,516	2,158	2,158	2,312	2,312
F	2.521	2.544	5.325	5.122	4.158	4.101
R^2	0.054	0.055	0.188	0.190	0.092	0.092

Notes: The table reports Huber-robust placebo regressions of households' absolute forecast errors $|FER| \equiv |R_{t+1} - F^i R_{t+1}|$ (columns 1-4) and back/nowcast errors $|BER| \equiv |R_t - B^i R_t|$ (columns 5-6), for stock market returns on the CAC-40 index over the next five or and last three years respectively, on our measures of informative social interactions. Columns 3-5 report results for households' absolute forecast errors conditional on back/nowcast errors. (^a) Age, gender, marital status and children at home. (^b) Education (college or more), region of residence, employment status, total wealth, income and savings distribution quartiles and borrowing/liquidity constrained status. (^c) The full set of Non-response (NR), Does-not-Know (DK) and Inconsistent (IC) categories is as specified in Table 8. Reference categories are: 18-34 year old, Female, less than college education, single, widow or divorced, out of the labor force, region 1 (living in Paris), borrowing and liquidity unconstrained, and the first quartiles of the total wealth, income and savings distribution, respectively. Robust standard errors are reported in parentheses. ***, ** and * denote significance at 1%, 5% and 10%, respectively. Source: merged TNS2014 and TNS2015 waves in France.

TABLE 7: Attenuation Bias

VARIABLES	(1) Pr(Stocks >0)	(2) %OC Inform. first stage	(3) Pr(Stocks >0)	(4) %OC Particip. first stage	(5) E(%FW >0)	(6) %OC Inform. first stage	(7) E(%FW >0)	(8) %OC Particip. first stage
%FC Inform.	0.0112*** (0.0036)	0.188*** (0.0099)			0.0701* (0.0406)	0.192*** (0.0099)		
%OC Inform.	-0.0103 (0.0150)	-			-0.1720 (0.1620)	-		
%FC Particip.			0.0084* (0.0050)	0.216*** (0.0093)			0.0621 (0.0506)	0.219*** (0.0097)
%OC Particip.			0.0038 (0.0199)	-			-0.0564 (0.2070)	-
SC Rel.Stand. Prof.+	n/s	0.055***	n/s	0.030***	n/s	0.051***	n/s	0.028**
SC Rel.Stand. Prof.-	n/s	-0.046***	n/s	-0.039***	n/s	-0.057***	n/s	-0.047***
FC Rel.Stand.vars. inc.: ^a	yes	yes	yes	yes	yes	yes	yes	yes
Expec.R	0.0072** (0.0031)	-0.0026 (0.0144)	0.0073** (0.0031)	0.0019 (0.0134)	0.106*** (0.0357)	-0.0031 (0.0154)	0.109*** (0.0364)	0.0033 (0.0150)
Risk Aversion	-0.0142** (0.0063)	0.0076 (0.0287)	-0.0138** (0.0062)	0.0146 (0.0277)	-0.1140* (0.0607)	-0.0059 (0.0297)	-0.1100* (0.0626)	0.0072 (0.0290)
%Pop. Inform.	-	0.187*** (0.01270)			-	0.184*** (0.0133)		-
%Pop. Particip.		-	-	0.164*** (0.0142)		-	-	0.167*** (0.0150)
Socio-demogr. inc.: ^b	yes	yes	yes	yes	yes	yes	yes	yes
Socio-econ. inc.: ^c	yes	yes	yes	yes	yes	yes	yes	yes
NR/DK/IC cat. inc.: ^d	yes	yes	yes	yes	yes	yes	yes	yes
Observations	2,525		2,525		2,294		2,294	
Log-likelihood	-9402		-9317		-11097		-11036	
LR χ^2 (p-value)	459.3 (0)		440.3 (0)		572.6 (0)		587.6 (0)	
First stage F-stat (p-value); R^2	54.31 (0); 0.55		45.65 (0); 0.51		49.65 (0); 0.55		41.99 (0); 0.51	
Wald test $\chi^2(1)$ (p-value)	0.468 (0.494)		0.0512 (0.821)		1.599 (0.206)		0.388 (0.533)	

Notes: The table reports marginal and conditional marginal effects for the probability of stock market participation and the share of financial wealth invested in the stock market conditional on participating instrumented for potentially endogenous outer circle information or behavior stemming from measurement error (odd numbered columns), as well as the corresponding results of first stage regressions (even numbered columns) of the outer circle information and behavior instrumented by population information and behavior respectively. The last line reports Wald exogeneity tests (and associated p-values) under the null of no-endogeneity, when the models are estimated jointly by ML. The second last line reports the first stage Fisher statistics (and associated p-values) under the null of no relevance, as well as the goodness of fit of the first stage regressions. (^a) FC Rel. Stand. +Profes., +Wealth and +Edu. (^b) Age, gender, marital status and children at home. (^c) Education (college or more), region of residence, employment status, total wealth, income and savings distribution quartiles and borrowing/liquidity constrained status. (^d). Reference categories are as in Table 2. Robust standard errors are reported in parentheses. ***, ** and * denote significance at 1%, 5% and 10%, respectively. Source: merged TNS2014 and TNS2015 waves.

TABLE 8: Summary statistics

VARIABLES	Patrimoine INSEE 2014-15	TNS 2014 & 2015 merged				Observations
	Mean	Mean	St.Dev.	Min.	Max.	
Pr(Stocks >0)	0.129	0.217	0.412	0	1	3,606
%FW	15	21.4 (5.324)	22.46 (14.53)	1 (0)	100	719 (2,891)
N in Social Circle	n/a	52.56	77.01	0	999	2,334
N in Financial Circle	n/a	3.160	6.746	0	100	2,243
% SC Particip.	n/a	10.74	15.72	0	90	809
% SC Informed	n/a	12.57	15.82	0	80	871
% FC Particip.	n/a	18.93	28.25	0	100	674
% FC Informed	n/a	20.50	27.59	0	100	740
% OC Particip.	n/a	13.43	17.21	0	100	526
% OC Informed	n/a	11.56	17.65	0	90.05	472
% Population Particip.	n/a	19.39	14.53	0	90	1,112
% Population Informed	n/a	22.88	16.69	0	100	1,171
SC Rel. Stand. Prof. +	n/a	29.34	27.02	0	100	734
SC Rel. Stand. Prof. -	n/a	23.76	23.24	0	100	734
FC Rel. Stand. Prof. +	n/a	36.88	35.03	0	100	518
FC Rel. Stand. Prof. -	n/a	18.73	25.61	0	100	518
FC Rel. Stand. Wealth +	n/a	1.775	0.653	1	3	2,261
FC Rel. Stand. Edu. +	n/a	1.916	0.663	1	3	2,275
Expec. R	n/a	1.62	8.944	-62.5	62.5	2,535
St. dev. Expec. R	n/a	6.699	7.082	0	38.7	2,535
D(StDev.ER=0)	n/a	0.343	0.475	0	1	2,743
Perc. R	n/a	3.607	12.04	-37.5	37.5	2,328
St. dev. Perc. R.	n/a	6.649	7.171	0	31.15	2,328
Risk aversion	n/a	34.90	11.76	0	40	3,670
Borrowing & Liq.Constr.	n/a	0.0292	0.168	0	1	3,670
Age <35	0.177	0.170	0.376	0	1	3,670
35 <Age <50	0.264	0.244	0.429	0	1	3,670
50 <Age <65	0.276	0.275	0.446	0	1	3,670
Age >65	0.283	0.311	0.463	0	1	3,670
Male	0.604	0.464	0.499	0	1	3,670
Married	0.732	0.602	0.490	0	1	3,670
Children at Home >0	0.372	0.241	0.428	0	1	3,670
College or more	0.363	0.376	0.484	0	1	3,670

Table 8: Summary statistics (continued)

VARIABLES	Patrimoine INSEE 2014-15	TNS 2014 & 2015 merged				Observations
	Mean	Mean	St.Dev.	Min.	Max.	
(continues from previous page)						
reg1	0.175	0.168	0.374	0	1	3,670
reg2	0.060	0.0635	0.244	0	1	3,670
reg3	0.083	0.0817	0.274	0	1	3,670
reg4	+	0.0826	0.275	0	1	3,670
reg5	0.166	0.0959	0.295	0	1	3,670
reg6	0.135	0.142	0.349	0	1	3,670
reg7	0.111	0.115	0.319	0	1	3,670
reg8	0.122	0.123	0.328	0	1	3,670
reg9	0.122	0.128	0.334	0	1	3,670
Employed	0.545	0.518	0.500	0	1	3,670
Self-employed	0.053	0.0349	0.183	0	1	3,670
Retired	0.359	0.311	0.463	0	1	3,670
Assets <74999	0.376	0.275	0.447	0	1	3,087
75000 <Assets <224999	0.242	0.319	0.466	0	1	3,087
224500 <Assets <449999	0.231	0.279	0.448	0	1	3,087
450000 <Assets	0.150	0.127	0.333	0	1	3,087
Income <11999	0.395	0.305	0.460	0	1	3,590
12000 <Income <19999	0.195	0.279	0.449	0	1	3,590
20000 <Income <29999	0.201	0.274	0.446	0	1	3,590
Income >30000	0.209	0.142	0.349	0	1	3,590
Saving=0	n/a	0.324	0.468	0	1	3,519
0 <Saving <999	n/a	0.293	0.455	0	1	3,519
1000 <Saving <4999	n/a	0.280	0.449	0	1	3,519
Saving >5000	n/a	0.103	0.305	0	1	3,519
NR(Assets)	n/a	0.159	0.366	0	1	3,670
NR(Income)	n/a	0.022	0.146	0	1	3,670
NR(Saving)	n/a	0.041	0.199	0	1	3,670
NR(SC Rel. Stand. Prof.)	n/a	0.332	0.471	0	1	3,670
DK(SC Rel. Stand. Prof.)	n/a	0.469	0.499	0	1	3,670
NR(FC Rel. Stand. Prof.)	n/a	0.352	0.478	0	1	3,670
DK(FC Rel. Stand. Prof.)	n/a	0.507	0.500	0	1	3,670
NR(FC Rel. Stand. Wealth)	n/a	0.384	0.486	0	1	3,670
NR(FC Rel. Stand. Edu.)	n/a	0.380	0.485	0	1	3,670

Source: 2014 INSEE 'Patrimoine' survey and authors' calculations on merged TNS 2014 & 2015 data set.

APPENDIX

A. MODEL DERIVATIONS AND ECONOMETRIC SPECIFICATION

Noisy Rational Expectations Equilibrium. We conjecture that the risky asset price has the form

$$p = \pi_0 + \sum_{j=1}^n \pi_j x_j - \gamma Z_n, \quad (23)$$

and imposing market clearing we have that $\sum_i D_i^* = Z_n$. 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 $\mathbf{S} \equiv \text{Cov}(R\epsilon) = R\Sigma R^T$, 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, $K = \text{diag}[k_1, \dots, k_n]$, 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. $\|W\|_\infty = o(n)$, i.e.

$$\lim_{n \rightarrow \infty} \frac{\|W\|_\infty}{n} = 0 \quad (24)$$

A2. $\lim_{n \rightarrow \infty} \frac{1}{n} \sum_{i=1}^n \frac{k_i}{\rho_i} = \beta + o(1)$. 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 $n \rightarrow \infty$, i.e.

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

A4. The limit

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

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

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

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 $n \rightarrow \infty$, are satisfied given the assumptions A1-A4.

The detailed steps of the proof are available in the Online Appendix.

Econometric Specification. We derive a first order approximation of expression (8) around $k_i^* = 0$. Rewriting expression (8) as (10), and rearranging, we obtain:

$$E(X|\mathcal{I}_i) = [1 - \psi(k_i^*)]\bar{X} + \psi(k_i^*)x_i \equiv f(k_i^*)$$

Then its approximation to the first order around $k_i^* = 0$ is $f(k_i^*) \approx f(0) + f'(0)(k_i^* - 0)$, or:

$$E(X|\mathcal{I}_i) \approx [1 - \psi(0)]\bar{X} + \psi(0)x_i + [\psi'(0)x_i - \psi'(0)\bar{X}]k_i^* = \bar{X} - \sigma^2(x_i + \bar{X})k_i^* = \iota_0 + \iota_{1i}k_i^*$$

where $\psi(k_i^*) \equiv k_i^* \left(\frac{1}{\sigma^2} + k_i^* + \frac{\beta^2}{\Delta^2} \right)^{-1}$ and hence,

$$\psi(0) = 0, \psi'(k_i^*) \equiv \left(\frac{1}{\sigma^2} + \frac{\beta^2}{\Delta^2} \right) \left(\frac{1}{\sigma^2} + k_i^* + \frac{\beta^2}{\Delta^2} \right)^{-2},$$

and $\psi'(0) = \sigma^2$ since $\beta(k_i^* = 0) = 0$. Therefore, $\iota_0 \equiv \bar{X}$ and $\iota_{1i} \equiv -\sigma^2(x_i + \bar{X})$ are constants. Recalling that $E(X|\mathcal{I}_i) \equiv Expec. R_i$, we obtain:

$$Expec. R_i \approx \iota_0 + \iota_{1i}k_i^*$$

and therefore

$$R_{t+1} - \text{Expec. } R_i = \kappa_0 + \kappa_1 k_i^*$$

where $\kappa_0 \equiv R_{t+1} - \iota_0$ and $\kappa_1 \equiv -\iota_{1i}$, the latter capturing the reduction in the forecast error that more/better connected individuals achieve, *relative to* unconnected individuals, for whom $k_i^* = 0$. Adding the additional covariates, τ_i , and appending an error e_i term to the above expression, yields expression (14).

B. DEFINITIONS OF DATA VARIABLES

Table 8 reports summary sample statistics for all the variables we have used for the analysis, and compares them to similar measures (when available) in the 2014-2015 *Patrimoine* INSEE Survey, collected by the French National Institute of Statistics (INSEE). This is a French Household Wealth Survey, which targets around 20,000 households randomly selected through a process that ensures representativeness of social categories at the national level. Respondents are interviewed face-to-face, and are asked to report households' real-estate, financial and professional assets and liabilities in France. It oversamples the rich (just as most national wealth surveys do, like the US PSID or the Italian SHIW), and has been fielded in 1986, 1991-1992 (*Actifs financiers*), 1997-1998, 2003-2004, 2009-2010 and 2014-2015 (*Patrimoine*) without a longitudinal dimension. Since 2017, and in partnership with the Banque de France, it inputs the French part of the Household Finance and Consumption Survey (HFCS), a harmonized system of wealth surveys supervised by the European Central Bank (ECB). From 2014, the French Household Wealth Survey takes place every three years, and contains a subsample with a longitudinal dimension. The new panel establishes, complementary to the face-to-face surveys, a short self-administered follow-up survey (internet/paper) between waves to reduce attrition. In addition to describing the distribution of assets and liabilities and their evolution, the surveys also contain comprehensive information on factors accounting for wealth accumulation: family and professional biography, inheritances and gifts, income and financial situation.

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

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

- ... will have increased by more than 25%
- ... will have increased by 10 to 25%
- ... will have increased by less than 10%
- ... will be the same
- ... will have decreased by less than 10%
- ... will have decreased by 10 to 25%
- ... will have decreased by more than 25%

Question C39 inquires respondent i about the subjective relative likelihood of occurrence, $p_{t+1,k}^i$, of each of the seven alternative scenarios, $k = 1, \dots, 7$. Each scenario represents a possible

outcome range for the index percentage change between t and $t + 5$, $R_{t+1}(5) \equiv \frac{P_{t+5}}{P_t} - 1$.³⁸ Questions C40 and C41 provide subjective upper and lower bounds for the percentage change, R_{\max}^i and R_{\min}^i respectively. The corresponding outcome ranges are:

$$R_{t+1} \in \left\{ \underbrace{[-R_{\min}^i, -25]}_{k=1}, \underbrace{[-25, -10]}_{k=2}, \underbrace{(-10, 0)}_{k=3}, \underbrace{\{0\}}_{k=4}, \underbrace{(0, 10)}_{k=5}, \underbrace{[10, 25]}_{k=6}, \underbrace{(25, R_{\max}^i]}_{k=7} \right\}$$

and respondents' subjective likelihoods are accordingly:

$$p_{t+1,k}^i \equiv \Pr^i(R_{t+1} \in k) = \Pr^i\left(\frac{P_{t+5}}{P_t} - 1 \in k\right), \forall i$$

and zero elsewhere, i.e. $R_{t+1} \in (-\infty, -R_{\min}^i) \cup (R_{\max}^i, +\infty)$. Table 7 reports summary sample statistics for respondents' answers regarding expectations about stock market returns, imposing a uniform distribution within the different outcome ranges. On average, households appear more pessimistic and uncertain than the historical record would predict.

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

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

- ... has increased by more than 25%
- ... has increased by 10 to 25%
- ... has increased by less than 10%
- ... has remained the same
- ... has decreased by less than 10%
- ... has decreased by 10 to 25%
- ... has decreased by more than 25%

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

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

³⁸We 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. 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). See Campbell et al. (1997) for details.

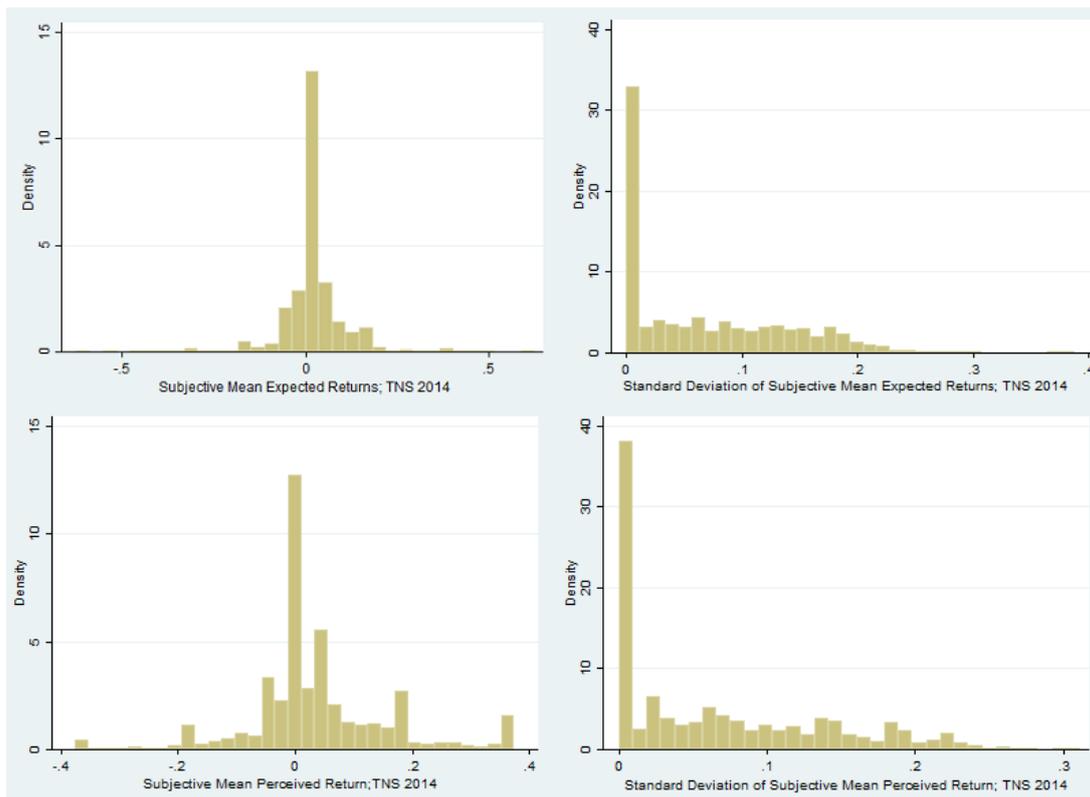


Figure 3: Histograms of the subjective mean: (a) expected five-year ahead cumulative return (top left panel) and its standard deviation (top right panel) and (b) perceived three-year cumulative realized return (bottom left panel) and its standard deviation (bottom right panel). *Source*: TNS2014.

Three years prior to the time when the survey was conducted (December 2011), the stock market index was only slightly above the floors reached after the dot-com and Lehman Brothers busts. But, between late December 2011 (CAC 40 = 3159.81) and late December 2014 (CAC 40 = 4252.29), the index had increased an overall 34.57%. Figure 1 in the main text shows the time window chosen within the wanderings of the CAC-40 index between 1990 and 2016. Table 7 reports summary sample statistics for respondents' answers regarding perceptions and beliefs about stock market returns, imposing a uniform distribution within the different outcome ranges. A striking finding is that households are on average also pessimistic regarding the most recently realized three-year cumulative stock market return (Dec. 2011-Dec. 2014). Although this might be due to imperfect memory given the unusually long horizon, it might also be related to the 2007 Lehman Brothers' bust being overweighted on respondents' memory (Hurd et al., 2011), even if outside the question's time window. The big spread around the realized three-year cumulative stock market perceived return came as no surprise, and it captures factual ambiguity. In addition, it is remarkable that it remains smaller than the spread around the expected five-year ahead cumulative stock market return.

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

Arrondel et al. (2014) report that categorical answers to frequency, variety and access spe-

cialized media, advice from professionals, as well as the number of stock market transactions carried over the last year, increase the likelihood of being factually informed. Interestingly, parents' stock ownership status ('cultural transmission'), parents' educational attainment or family background do not increase the odds of being factually informed, and actually significantly decreases them for those who follow family advice. Since those who follow friends' advice are more likely to be informed, they interpret the evidence as being consistent with social interactions being instrumental in gathering information (as in Hong et al., 2004). On the other hand, a measure of optimism ('being lucky in life') has a negative impact on being informed, indicating that an 'overconfidence bias' is not present once gender is conditioned upon: although males appear better informed, supporting more optimistic forward looking expectations, optimists appear consistently worse informed. On the basis of that finding, they argue that the findings of Biliias, Georgarakos and Haliassos (2010), consistent with inertia in households' portfolios, can be reconciled with Guiso and Jappelli's (2005) findings, consistent with excess trading even amongst the general population. Importantly, they do not find evidence of temporal or risk preferences determining information sets, in line with Van Nieuwerburgh and Veldkamp (2010). In addition, and although total wealth does not increase the odds of being informed, income does, in line with a costly information acquisition interpretation (Peress, 2004). Finally, they report that optimists and low income/income constrained respondents are less likely to be informed, consistent with rational inattention theory (Sims, 2003). Overall, those findings support probabilistically elicited perceptions as a sensible measure of factual information.

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

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

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

B.3. Population, social and financial interactions. These variables are described in detail in section 3. Summary statistics for questions C1, D1, C6, C7 and D16 are presented in Table 7.

B.4. Measures of social relative standing. The survey contains four measures of the respondent's relative standing in terms of social circle and financial circle outcomes:

SC Rel. Stand. Profes.: In the survey (question C5), the respondent is asked about the percentage shares of people in the respondent's social circle that have a professional status above, similar, or below the respondent's, labelled '*SC Rel. Stand. Profes. +*', '*SC Rel. Stand. Profes. =*', or '*SC Rel. Stand. Profes. -*' respectively. Since answers are asked to add up to 100, the reference category is '*SC Rel. Stand. Profes. =*'. About 47% of respondents chose the option to tick the box conveying '*I do not know*', which informs the corresponding '*DK(SC Rel. Stand. Profes.)*' dummy variable in Table 7. Non-respondents account for 33%, and are coded as '*NR(SC Rel. Stand. Profes.)*'.

FC Rel. Stand. Profes.: In the survey (question D6), the respondent is asked about the percentage share of people in the respondent's financial circle that have a professional

status above/similar/below the respondent's, labelled '*FC Rel. Stand. Profes. +*', '*FC Rel. Stand. Profes. =*', or '*FC Rel. Stand. Profes. -*' respectively. Since answers are asked to add up to 100, the reference category is '*FC Rel. Stand. Profes. =*'. About 51% of respondents chose the option to tick the box conveying '*I do not know*', which informs the corresponding '*DK(FC Rel. Stand. Profes.)*' dummy variable in Table 5. Non-respondents account for 35%, and are coded as '*NR(FC Rel. Stand. Profes.)*'

FC Rel.Stand. +Wealth: In the survey (question D7), the respondent is asked about her/his relative standing in terms of wealth relative to the average wealth of the respondent's financial circle, and is given three options: 'below the average', 'approximately at the average', or 'above the average'. Responses were coded as ordered categories in increasing order from 1 to 3. About 38% chose not to respond, and are coded as '*NR(FC Rel.Stand. +Wealth)*' in Table 7.

FC Rel.Stand. +Edu.: In the survey (question D8), the respondent is asked about her/his relative standing in terms of educational attainment relative to the average educational attainment of the respondent's financial circle, and is given three options: 'below the average', 'approximately at the average' or 'above the average'. Responses were coded as ordered categories in increasing order from 1 (below) to 3 (above). Around 38% are non-responses, which are coded as '*NR(FC Rel.Stand. +Edu.)*' in Table 7.

B.5. Demographics and other control Variables.

Endowments.

Total wealth: In the survey (question C29), the respondent is asked which of the ten predefined available brackets corresponds to the household's non-human wealth, including housing, estates and professional assets (without excluding debt):³⁹ 'Less than 8,000', 'between 8,000 and 14,999', 'between 15,000 and 39,999', 'between 40,000 and 74,999', 'between 75,000 and 149,999', 'between 150,000 and 224,999', 'between 225,000 and 299,999', 'between 300,000 and 449,999', 'between 450,000 and 749,999' and '750,000 or more'. Total wealth is given in Euros. From the empirical distribution we obtain total wealth quartiles, the bounds of which are given by '74,999', '224,999' and '449,999'. The reference category is the first quartile, 'less than 74,999'.

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

Income: For the income of the household, the survey (question A12) asks the respondent which of the nine predefined available brackets better corresponds to her situation: 'Less than 8,000', 'between 8,000 and 11,999', 'between 12,000 and 15,999', 'between 16,000 and 19,999', 'between 20,000 and 29,999', 'between 30,000 and 39,999', 'between 40,000

³⁹If 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.

and 59,999', '60,000 or more' and 'No income'. Income refers to the respondent's annual income (earnings, pensions, bonuses, etc.) in Euros, net of social contributions but before personal income taxes.⁴⁰ In addition, TNS reports also the net gross monthly income of the household, in Euros. From the empirical distribution, we obtain the income quartiles the bounds of which are given by '11,999', '19,999' and '29,999'. The reference category is the first quartile, 'less than 11,999'.

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

Preferences.

Absolute risk aversion: The following question is asked to the respondent: 'If someone suggests that you make an investment, \tilde{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 $u^i(\cdot)$, from the following equality:

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

The coefficient of absolute risk aversion can be then obtained from a second order Taylor expansion, as $A_i(w_i) = 2(5000 - Z_i)/(5000^2 + Z_i^2)$, where Z_i is the amount that the respondent declares to be willing to invest. Those who declare $Z_i < 5000$ are risk-averse $Z_i = 5000$, are risk-neutral and $Z_i > 5000$ are risk-lovers. The outcome range for the coefficient of absolute risk aversion $A_i(w_i)$ is $[0, 40]$. A total of 3,335 respondents answered the question, with a mean response of 38.40 and a median value of 39.92. Fig. 4 displays the histogram of responses, which is very skewed to the left but remains within the range responses found in the literature. Further details regarding the measure of absolute risk aversion can be found in Guiso and Paiella's (2008) work.

Demographics.

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

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

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

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

⁴⁰When the survey took place, income in France was not taxed at the source.

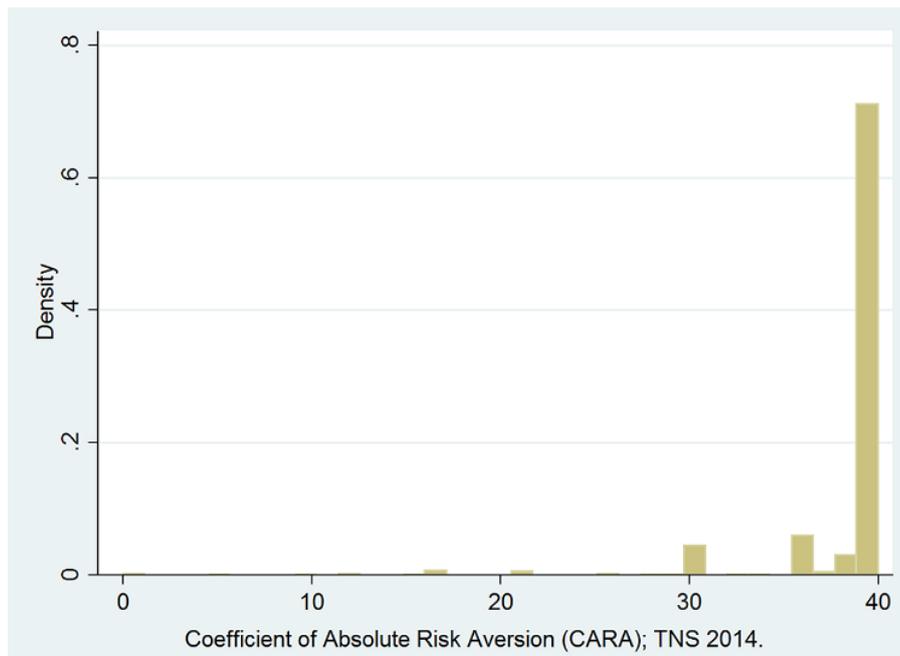


Figure 4: Histogram of responses to the hypothetical lottery that enables elicitation of the respondent's coefficient of absolute risk aversion (CARA). *Source:* TNS2014.

Constraints.

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

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

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

Information.

Education is 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).