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

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

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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 large scale and systemically important events, it is natural to ask: what is the role of social interactions and peer effects for the spread of financial behavior in the general population?

It is well understood that there are two broad channels through which social interactions may affect individuals' decisions. The first channel is one of direct information flow, i.e. of direct communication and dissemination of information and knowledge between individuals. The second is a channel of imitation of the behavior of peers, either mindful or mindless. Imitation of peers is mindful when they are perceived to be knowledgeable or well-informed and thus their actions convey useful information. In contrast, imitation is mindless when the actions of peers convey no intrinsic information. While both types of imitation may be widespread in practice, they are difficult to disentangle. But being able to disentangle informative social interactions, namely the exchange of information and mindful imitation on the one hand, from mindless imitation on the other, is of fundamental importance for both the understanding of financial and aggregate macroeconomic outcomes, and the design and conduct of public policy.[1]

In this paper, we focus on individuals' decisions on stock market participation and exposure. We examine whether social interactions matter for such decisions and investigate whether there is a significant role for informative social interactions in stockholding behavior alongside a possible role for mindless imitation. Our findings support that, in a financially developed economy with a mature stock market, pure information does indeed flow between individuals who interact socially when it comes to stock market participation and conditional portfolio shares. Our work makes two important contributions. First, we provide evidence of a sizeable and statistically significant information channel, operating on different levels: perceptions of realised returns, expectations of future returns, and stockholding behavior conditional on expectations. Our results also suggest that imitation in stock markets may sometimes be present, but is not the most important channel through which

[1] This was also highlighted in a recent keynote lecture by Christopher Caroll, titled '*Heterogeneity, Macroeconomics and Reality*', at the Sloan-BoE-OFR Conference on Heterogeneous Agent Macroeconomics, U.S. Department of the Treasury, Sep. 2017.

social interactions influence stockholding behavior.[2] Second, our findings point to a clear mechanism by which social interactions within a competitive market affect individuals' expectations of stock market returns and stockholdings. Specifically, we find evidence of an informational channel: social interactions improve individuals' perceptions of realised stock market returns, which in turn influence expectations and thereby, stock market participation and conditional portfolio shares. Overall, our findings provide support for the view that social interactions do not simply produce mindless imitation of financial behavior of the social circle, but allow the transfer of relevant knowledge.

Broadly, our strategy for establishing the presence of an information channel can be summarized as follows. First, we set out a theoretical framework for analyzing stock market investment decisions that allows for information dissemination via social interactions, within a competitive market setting. Based on this framework, we derive a set of well-defined testable predictions. With these predictions in hand, we design and field a unique and novel survey in order to collect data to test these predictions and empirically examine how robust they are.

Next, we provide a detailed description of how we establish the presence of an information channel for stock market decisions. The starting point of our analysis is to model direct communication and information dissemination between individuals, within a large efficient financial market.[3] Within that framework, 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. Such a framework extends Ozsoylev and Walden (2011) to individual heterogeneity in both risk preferences and signal precisions, in line with available empirical evidence. Heterogeneity in risk preferences allows us to distinguish between risk and information driven financial decisions.[4] Heterogeneity in signal precision provides a platform for distinguishing individuals that are well informed about the stock market from those that are less informed. A key prediction of the model is therefore that individuals with higher risk-adjusted 'connectedness', i.e. those with

[2] Our results are consistent with those of Banerjee, Chandrasekhar, Duflo and Jackson (2013) who show this in context of small markets in financially developping economies, in particular Indian villages.

[3] Recent work by Blume, Brock, Durlauf and Jayaraman (2015) provides a rigorous derivation of the equilibrium underpinnings of social utility driven (or endorsement, or imitation based) peer effects for the standard linear-in-means econometric specification of social interactions models. However, no such micro-foundation exists for information driven peer effects.

[4] Cabrales, Gossner and Serrano (2013 and 2017) show that in equilibrium, more risk tolerant individuals are willing to pay *more* for information; therefore, less risk averse agents may have more and/or better informed social connections.

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.

With this prediction in hand, we design, field and exploit novel survey data from a representative sample by age, asset classes and wealth of the population of France, collected in two stages, in December 2014 and May 2015. The survey questionnaire provides measures of stock market participation and risky portfolio share, risk attitudes, connectedness within the network of peers, perceived characteristics of respondents' peers stock market participation and information, and importantly, probabilistically elicited subjective expectations and perceptions of stock market returns. It also contains specific questions designed to obtain quantitative measures of relevant network characteristics that enable identification of information network effects on financial decisions from individual answers. Finally, the questionnaire contains a very rich set of covariates for socioeconomic and demographic controls, preferences, constraints, and access and frequency of consultation of information sources, typically absent from empirical studies of social networks.

The survey was designed with four features in mind. First, the mechanism through which social interactions matter for financial decisions can be empirically identified from respondents' answers to questions on beliefs and perceptions of stock market returns, when combined with data on measures of access and frequency of consultation of both publicly and privately available information sources (see Blume, Brock, Durlauf and Jayaraman, 2015). Second, in order to circumvent Manski's (1993) reflection problem that arises when social interactions are identified empirically from linear-in-means econometric specifications (see Blume, Brock, Durlauf and Ioannides, 2011), we do not control for average *actual* peer behavior but for respondents' *perceived* peer behavior.[5] Third, the survey is done over a representative sample of a population of a financially developed country (namely France), with a mature stock market and abundant publicly available information. Fourth, our main identification strategy for disentangling knowlegde transfer, mindful imitation, and mindless imitation, is based on reported perceptions of respondents regarding

[5]When respondents' preferences contain a social utility component, peer behaviour affects individual behaviour through the individual best response (Blume et al. 2011, 2015). However, when the social utility component is absent from individual preferences, our theoretical framework implies that peer behaviour and information enter individual best responses only through expectations of returns, i.e. only to the extent that they contain some information. Therefore, and since the stock market is non-manipulable from an individual's perspective, peer information or behaviour has no direct influence on individual behaviour and there is no purely informative endogenous peer effect.

the stock market behavior and information of three circles: the *financial circle*, i.e. peers with whom they discuss financial matters; their overall *social circle* of friends and acquaintances; and the overall *population*, about whom they have general views without systematic social interaction.[6] We elaborate further on this final feature next.

Our theoretical framework incorporates heterogeneity in signal precision, which allows for the possibility that social interactions with one's peers may be more or less informative, depending on how well informed or knowledgeable one's peers are. Using the responses about the financial and social circles, we can construct respondents perceptions about the behavior and information of peers from the *outer circle*. We think of a respondent's outer circle as the subset of the social circle that is the complement of the financial circle. i.e., those peers with whom respondents may interact with socially, but do not discuss own financial matters. Within-individual variation in the responses regarding the behavior and information of the two components of a respondent's social circle (financial and outer) allows us to identify *informative* peer effects on the respondent's own behavior, expectations and perceptions about the stock market, while controlling for how the respondent perceives others in general (the overall population). Additionally, within-individual variation in the responses regarding the same attributes of now the whole social circle and the overall population enables identification of overall social interactions effects on individual behavior, expectations or perceptions about the stock market.

This novel *triple circle* methodological approach helps us separate both pure information exchange from mindful imitation, and mindful from mindless imitation, while controlling for unobserved factors influencing how the respondent perceives others and the economy in general. We exploit information on respondent perceptions of the three circles in a number of different ways. First, by controlling for these perceptions in regressions; second, by conducting placebo tests, where responses about the circles are reshuffled for respondents of the same age, education, and location; and third, by modeling the joint decision to have a financial circle and to participate in the stock market.

We find that respondents' perceptions about the shares of their financial circles that are informed about the stock market or actively participating in it are systematically related to respondents' perceptions and expectations of stock market returns, the probability of stock market participation, and the risky portfolio share conditional on participation. Respondents who perceive their financial circles to be

[6]In our data, we find that the financial circle 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 the social circle in France.

more informed or more widely participating in the stock market have perceptions of returns that are closer to the truth. In contrast, the effects of respondents' perceptions about how informed their outer social circles and the population are on expectations of stock market returns are statistically insignificant. Importantly, the extent to which respondents perceive their financial circle to be informed about or participating in the stock market affects expectations of returns only through improved perceptions of (recently realised) returns. If the effect of social interactions on stockholding were to run only through expectations of returns without affecting perceptions, then we would not be able to exclude the possibility that individuals simply mimic the optimism of those they interact with, without in fact being better informed about the stock market. Our finding that the effect on expectations runs solely through improved perceptions about past stock market returns strongly corroborates the presence of an information effect of peers on stockholding behavior.

While the relevance of information in the financial circle points to informative interactions, the relevance of participation allows for both information exchange and mindful imitation of peers perceived to be knowledgeable about financial matters. Our analysis also indicates traces of mindless imitation in stockholding behavior. In particular, we find that respondents may be influenced by the financial behavior of those in their outer social circle, even though they do not consider them knowledgeable in financial matters. Interestingly, this effect does not run either through perceptions or expectations. Based on this, and on the fact that respondents do not engage in financial discussions with their outer social circles by construction, this can be interpreted as mindless imitation that does not permeate as many layers of the stockholding decision as informative interactions and mindful imitation of informed peers do.

We employ a number of robustness checks that corroborate our main findings. First, to assess the relevance of unobserved heterogeneity, we make use of the triple circle approach. As a first line of attack, we split the social circle of respondents into financial and outer circles and do placebo tests. If indeed respondents and their social circles all follow and/or invest in the stock market (or refrain from doing so) because people tend to socialize with those that are similar to them and face common unobserved factors, then we would expect to see positive and significant effects of the knowledge and participation of both the financial and outer circles on perceptions, expectations, participation, and conditional portfolio share of respondents. Lack of statistical significance of perceptions regarding how informed the outer circle is argues against unobserved heterogeneity. By additionally controlling for perceptions regarding the population, we are controlling for how respondents' see others in general and we get the differential effect of belonging in the financial or the outer social circle. However, it can be argued that lack of statistical significance of outer circle variables can be caused by attenuation bias: respondents are less knowledgeable about their outer circle as they do not discuss financial matters with them. To guard against this possibility, we focus on the financial circle only and conduct placebo tests reshuffling perceptions of the financial circle among respondents of similar age, education, and region of residence. Although these reshuffled perceptions come from the same age-education group, they fail to exhibit statistical significance, supporting the notion that unobserved heterogeneity is not the source of the results.

Moreover, we allow for the possibility of selection bias, measurement error and functional form misspecification. For the first of these three possibilities, we allow respondents to jointly select their financial circle and whether to invest in stocks or not, but fail to find any evidence for correlated unobserved factors in these two decisions. For the second, we repeat the analysis exploiting individual responses regarding the perceived population stock market participation rate and percentage informed as an instrument for outer circle peer behavior and peer information, to find that the null hypothesis of no measurement error cannot be rejected. For the third possibility, we allow for interaction terms between financial and outer circle perceived shares of informed and participating peers with expectations of returns, and find that the estimated interaction terms are never statistically different from zero, while the estimated non-interacted terms remain present, remain statistically significant and similar in magnitude.

Last, we note that given the anonymous nature of stock holding and trading, our analysis is not limited by the fact that we cannot 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. We elicit perceptions that respondents have and on the basis of which they make stockholding choices, even though we cannot observe the extent to which individual perceptions about peer information or behavior correspond to their objective counterparts.

Our work relates to different strands of literature, from social interactions and networks to financial literacy. Within the growing literature examining peer and network effects on asset and debt behavior of households, such as Duflo and Saez (2002, 2003), Hong, Kubik and Stein (2004), Kaustia and Knüpfer (2012), Georgarakos, Haliassos and Pasini (2014), Beshears, Choi, Laibson, Madrian and Milkman (2015), Bailey, Cao, Kuchler and Stroebel (2016), Girshina, Mathae and Ziegelmeyer (2017), Haliassos, Jansson and Karabulut (2018) or Ouimet and Tate (2017), we connect to the financial literacy literature through the key role perceptions about returns play as a measure of financial knowledge (e.g. Lusardi, Michaud and Mitchell, 2016; Campbell, 2016; Lusardi and Mitchell, 2014). Our work also relates to a fast growing literature that examines the effect of subjective expectations on individual economic and financial behavior, summarized by Hurd (2009) or more recently, by Greenwood and Schleifer (2014), and its important consequences in the aggregate, as in e.g. Carroll (2003). More generally, Manski (2017) summarizes the progress and discusses the promise of measurement of macroeconomic expectations. Other recent advances in the literature include Bordalo, Gennaioli, Ma and Shleifer (2017), Fuster, Perez-Truglia, Wiederholt and Zafar (2018) and Giustinelli and Shapiro (2018). Last, it is also closely related to the literature on the effects of social imitation and influence on financial behavior in competitive markets within the larger literature on social and information networks, see e.g. Jackson (2008).

Most related to our work is that of Bursztyn, Ederer, Ferman and Yuchtman (2014), who conduct a field experiment in collaboration with a Brazilian brokerage firm in order to disentangle endorsement from information peer effects on the willingness to invest in a brand new financial product. For such a product, they conclude that both motives are important in individual financial decision making and that the social learning channel is relatively more important than the social utility channel amongst more sophisticated investors. Also related is the experimental work by Banerjee, Chandrasekhar, Duflo and Jackson (2013) who study a newly introduced micro-finance program in rural India and conclude that most peer effects on the take-up rates of the program are due to an information channel. Although the tight control of information flows in both these field experiments helps separate information from social effects, it may artificially magnify the importance of each signal, possibly biasing upwards the estimate of information effects relative to what would have been observed for well-established financial products (stocks) in a mature financial market, where investors may be informed through a multitude of channels.[7] Finally, recent empirical work by Ozsoylev, Walden, Yavuz and Bildik (2014) attempts to identify an empirical (professional) investor network by assuming that time proximity of transactions implies network connectivity between investors. The similarities and differences with these papers are further evaluated, in light of our findings, in Section 4.

The paper is structured as follows. The next section presents the theoretical framework and derives key predictions. Section 3 describes the survey design in

[7] The same observation is also made by Manski (2017): he argues that the exogenous provision of a new financial product or information about it assumes understanding of the underlying reasons why individuals did not gather the information on their own.

detail. Section 4 presents our empirical results. Section 5 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 $\bar{Z} > 0$.[8] The final wealth of the agent is

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

where ω_{0i} is the initial wealth of agent i. Agent i chooses D_i units of the risky asset to maximize expected utility from final wealth, conditional on his information set $\mathcal{I}_i$. We assume constant absolute risk aversion (CARA) preferences $u\left(\omega_i\right) = -e^{-\rho_i \omega_i}$, where ρ_i is the absolute risk aversion of agent i. Agent i thus solves the problem

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

Therefore,

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

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

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 $a_{ij} = 1$.

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

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.[9] 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.[10] The typical element of matrix G is then

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

in other words, $G = A\Sigma^{-1}$, where $\Sigma = diag\left\{s_1^2, ..., s_n^2\right\}$. We note that G represents a weighted and directed network. The pooled payoff signal x_i for agent i is:

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

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

$$\mathcal{I}_i = \{x_i, p\}, \forall i = 1, ..., n \tag{5}$$

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

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

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

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

[10] Proportional 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).

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 $n \to \infty$). The average connectedness β of the economy-wide information network as the economy grows, is defined via the assumption that

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

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

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

where

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

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 $n \to \infty$, the expected return for an investor i is given by

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

where $k_i^* = \lim_{n\to\infty} k_i$. This suggests that larger connectedness k_i^* implies that investors expectations react more strongly to their pooled signal. Moreover, in equilibrium, the asymptotic demand for the risky asset by an agent i can be expressed in the two following ways:

$$D_i^* \equiv \frac{1}{\rho_i}\left(\frac{1}{\sigma^2}+k_i^*+\frac{\beta^2}{\Delta^2}\right)\left(\mathbb{E}\left(X|\mathcal{I}_i\right)-p\right) \tag{9}$$

or

$$D_i^* = \frac{\hat{\rho}}{\rho_i}\left(\frac{\bar{X}\Delta^2+\bar{Z}\beta\sigma^2}{\hat{\rho}\sigma^2\Delta^2+\sigma^2\beta}\right)-\frac{\hat{\rho}}{\rho_i}\left(\frac{\Delta^2}{\sigma^2\left(\hat{\rho}\Delta^2+\beta\right)}\right)p+\frac{k_i^*}{\rho_i}\left(x_i-p\right). \tag{10}$$

Expressions (8)-(10) will guide our empirical investigation of informative social interactions. Expression (9) 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 $E\left(X|\mathcal{I}_i\right)$ in (8), and second, a direct positive effect of risk-adjusted connectedness k_i^*/ρ_i appearing in the first parenthesis of (9). 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 obtained in equilibrium by agents that are more and/or better connected, adjusted by the agent's risk aversion. The second expression (10) again decomposes potentially two channels via which individual connectedness can affect demand: directly, via the positive effect of k_i^*/ρ_i, and indirectly through its effect on the excess return (i.e. within x_i).

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 that we seek to empirically identify exploiting our survey data. 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).[11]

We also highlight here that both the expressions for expected returns (8) and equilibrium individual demands (9) - (10) 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 to empirically identify an information peer effect and the three expressions (8)-(10) will be the basis of our empirical design and specifications.

3. Survey Design

In this section, we provide a brief description of the survey design and the specifically designed questions we exploit. More detailed information about both is provided in Appendix B. The survey is part of an ongoing survey of the French population administered by Taylor-Nelson Sofres (TNS). We design and exploit data from two linked questionnaires that were fielded in December 2014 and May 2015 respectively. The first questionnaire (2014 wave) contains questions that provide very 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 (2015 wave) contains a variety of questions that specifically aim at gathering information about respondents' social and financial circles. These include questions on of respondents' perceptions of how informed their circles are with respect to the stock market and how heavily they participate in it, as well as similar questions regarding their perceptions of overall population behavior, in terms of information about and participation in the stock market. In addition, respondents are asked to report their perceived relative standing vis-à-vis their peers 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

[11] Heterogeneity 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.

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%. The relevant questions that inform our empirical analysis can be grouped in four sets, which we describe below.

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

The second set of questions asks respondents to state their expectations and perceptions about a public non-manipulable event (e.g. the expected return on a buy-and-hold portfolio that tracks the evolution of the stock market index, CAC-40, over a five-year time window).[12] The recent literature on measuring expectations privileges the use of probability questions rather than eliciting point expectations or the traditional qualitative approach of attitudinal research (Manski, 2004). Answers to such questions are then used for understanding whether expectations and outcomes are related, and for evaluating whether individual behavior changes in response to changes in expectations. Crucially, we also include questions that inquire respondents about their perceptions regarding the most recent realization of an analogous measure (e.g. the most recent realized cumulative return on a buy-and-hold portfolio that tracks the evolution of the stock market index over a three-year horizon). The questions in this second set are designed with the following four goals in mind. First, the use of five years as a forecasting horizon helps untie expectational answers from business cycle conditions prevailing at the time of fielding the surveys, to better capture the historic average upward trend of the stock market index, and inertia in portfolio management (e.g. see Bilias, Georgarakos and Haliassos, 2010). The latter is important, since it remains an open question with what horizon in mind households invest in the stock market. Second, probability densities are elicited on seven points of the outcome space, instead of just two points of the

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

cumulative distribution functions, to obtain more precise individual estimates of the relevant moments and of the uncertainty surrounding expectations.[13] Third, we exploit data from a representative sample by age (while for example, Dominitz and Manski, 2007, report results only for the elderly). Fourth, probabilistic elicitation of the most recent cumulative stock market return over a three-year horizon provides a quantitative measure of households' degree of awareness of 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] We use responses to questions C39 and C42 (from TNS2014) to generate variables *Expec. R* and *Perc. R* respectively, which in turn are used as proxies for expected conditional returns $\mathbb{E}\left(X|\mathcal{I}_i\right)$ and for perceptions of realized returns (based on signals) x_i.

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

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

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

Of the 2,587 respondents that returned the TNS2015 questionnaires, about 90% and 87% answered questions C1 and D1 respectively. The average number of people in the respondents social circles and financial circles is 52.5 and 3.1 people respectively. About half of the valid responses for question D1 were zero, so we 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

[13] This follows the methodology of the Survey on Household Income and Wealth (SHIW) conducted by the Bank of Italy, e.g. Guiso, Jappelli and Terlizzese (1996).

[14] Also, Armantier, Nelson, Topa, Van der Klaauw and Zafar (2016) document substantial differences across households regarding the most recent US inflation rate. 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.

framework and predictions, which are only relevant under the assumption of sufficient network sparsity, i.e. the network is not too dense in terms of number of links.

Question C1 is formulated with the network of social acquaintances in mind, as described by adjacency matrix A in Section 2. For respondent i, the answer to C1 provides an approximation of the respondent's degree, defined by $\sum_{j=1}^{n} a_{ij}$. Question D1 defines a subset of the people from the respondent's social circle, and is formulated in order to generate broadly a proxy for the elements of matrix G, i.e. a statistic of whether information about the stock market is passed on from acquaintance j to respondent i. Question D1 thus invites respondents to describe a possibly smaller 'inner' circle of peers with whom they discuss financial matters (the financial circle), and to distinguish them from the outer circle of peers with whom they interact socially without necessarily discussing finances. It leaves open the possibility that the respondent does not have such an inner circle, and this choice is modelled explicitly in the later part of our empirical analysis.

With reference to the theoretical model, 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.

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, 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:

[15] A similar question format has been successfully exploited by researchers at the Dutch National Bank and at the University of Tilburg (CentER Panel) when identifying social interactions on individual outcomes, since it helps in overcoming the reflection problem identified by Manski (1993). The reflection problem refers to the impossibility of separately identifying the effect of peers' *choices* (endogenous or peer effects) from the effect of peers' characteristics (contextual effects) on individual outcomes, when individual and peers' choices are made simultaneously and as a function of common contextual factors. Here, instead of considering peers' actual choices, we exploit the variation in individual perceptions about peers' choices (e.g. stockholding status), which when combined with individual perceptions about peers' characteristics (e.g. peers' information or respondents' relative standing in terms of education, wealth or professional status), enables identification. See Blume et al. (2011, 2015) for additional details.

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

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

Of the 2,587 respondents that send back the TNS2015 questionnaires, about 96% and 88% of respondents provided valid answers for questions C7 and D16 respectively.[16] The cross-sectional average point estimates for the perceived percentage of the social and financial circle that invests in the stock market is 10.7% and 18.9% respectively. Also, the cross-sectional average point estimates for the perceived percentages of the social and the financial circles that follows the stock market are 12.6% and 20.5% respectively. These questions define directly variables $\%SC\ Particip.$, $\%FC\ Particip$, $\%SC\ Inform.$ and $\%FC\ Inform.$ The perceived percentage of the outer circle of a respondent that invests in or is informed about the stock market is obtained from

$$\%OC\ Particip. \equiv \frac{C1 \times C7i - D1 \times D16i}{C1 - D1}, \tag{11}$$

$$\%OC\ Inform. \equiv \frac{C1 \times C7ii - D1 \times D16ii}{C1 - D1}. \tag{12}$$

Additionally and similarly, questions C6i and C6ii ask respondents about the proportion of the French population that invest and are informed about the stock market, respectively.[17] Surprisingly, the cross-sectional average point estimate for 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.

The final set of questions ask respondents to place themselves relative to others in their circles, both social and financial. With these, respondents state how the see themselves in terms of wealth, education and professional standing relative to their peers (for details see Appendix B4).

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

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

[17] In answering each of the questions, the respondent was also given the option to tick the box '*I do not know,*' (DK). About 54% and 52% chose this option for questions C6i and C6ii respectively. About 3.1% chose not to answer these questions, and are accordingly coded as 'non-responses,' (NR).

answer to C1 - answer to D1) respectively. Other abbreviations used throughout the paper are summarized in Table 1. Definitions, exact question statements and detailed explanations on the variables and the survey questions can be found later in the paper and in Appendix B. Table 7 provides summary statistics for the variables we use in the analysis.

4. Empirical analysis

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

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

For respondents who declare having formed a financial circle, we use expressions (11) and (12) to compute their implied perceptions regarding members of their social circle with whom they do not discuss finances. The distinction between a financial and an outer circle is very useful for checking whether our results might be caused by unobserved heterogeneity rather than peer influences; and in distinguishing between exchange of information and mindless imitation of stockholding behavior. Specifically, it is possible that there are unobserved factors influencing the respondent's stock market expectations, perceptions or behavior, as well as whether their peers are informed about, or participating in the stock market. These unobserved factors might induce a correlation between responses and peer attributes without implying any effect from peers on respondents. If respondent stock market expectations, perceptions, or behavior reflect simply unobserved dimensions along which respondents are similar to their peers, we would expect correlations to be present, whether we consider the financial circle or the outer social circle not privy to financial matters. If, however, only the financial circle, but not the outer circle matters for subjective expectations, perceptions, or behavior related to stockholding, then this is evidence against unobserved heterogeneity creating the empirically observed relationship. Furthermore, the within-respondent variation in peer groups that we exploit is conditional on variation across respondents in population-wide market outcomes, to guard against the possibility of social circle selection and unobserved correlated effects driving our peer effect results, within a highly volatile, efficient and competitive market environment.

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

We also note here that the survey questions elicit the shares of informed and participating peers in the financial and overall social circles only. We use these two responses to construct the corresponding share of peers in the outer circle, i.e., the complement of the financial circle to the overall social circle. As our approach is indirect, it can sometimes lead to outer-circle shares that fall below zero or exceed 100%. When this happens, we adopt a conservative approach to potential inconsistency: we set both the direct response on the financial circle and the implied for the outer circle to 'missing observation', and we introduce an inconsistency dummy variable (IC) to flag such observations.[18] All reported estimates on the two circles explicitly control for observed inconsistencies in responses.

4.2. Expectations and perceptions. Existing empirical studies of peer effects on financial behavior focus on outcomes, such as stockholding, retirement saving, or debt outstanding. We begin our analysis by investigating the role of social interactions for the formation of subjective return expectations about the future, as well

[18] Exception is made of those inconsistencies that are attributed to rounding, because of low numbers reported to question D1. With this criterion in place, a total of 19 observations are excluded from the IC category.

as of perceptions regarding past stock market performance. As established, expectations are an important determinant of the demand for risky assets, this analysis is interesting both in its own right and as a component of the link to stockholding behavior.[19]

To investigate the empirical relevance of perceptions regarding interacting peers for subjective expectations of stock market returns over the next five-year period, we consider an approximate linear version of expression (8), which suggests two empirical specifications:

$$Expec.\ R_i = \kappa_0 + \kappa_1 k_i^* + \boldsymbol{\tau}_i \boldsymbol{\kappa} + e_i \tag{13}$$

and

$$Expec.\ R_i = \kappa_0 + \kappa_1 D_i^e + \boldsymbol{\tau}_i \boldsymbol{\kappa} + e_i, \tag{14}$$

where k_i^* is an indicator of connectedness to the peer circle, 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 individual perceptions about peer characteristics, e_i is an individual zero-mean error term distributed normally conditional on covariates and the same coefficient symbols are used for notational economy but not to imply equality of coefficients.[20]

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

As a first approach to handling this problem, we distinguish perceptions about the two peer circles: the inner, financial circle with whom respondents report that

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

[20] To control for endorsement peer effects that can rationalize mindless imitation (e.g. due to a preference to conform), we include measures of the respondent's perceived relative standing in terms of average peer education, average total wealth and professional status with respect to the social and financial circles.

they discuss financial matters; and the rest of their social circle with whom they report that they do not discuss such matters. Moreover, we also control for individual perceptions of market-wide characteristics unrelated to peer behavior, but that might be driving asset prices, like an increase in the proportion of the overall population investing in or being informed about the stock market.

We then investigate whether either share is significantly related to the respondent's subjective expectation about future stock market returns, after controlling for a range of observable respondent characteristics. By splitting the social circle into a financial circle and an outer circle, we are able to apply a 'double circle' methodology to identification. Additionally, by including in the controls respondents' perceptions about population-level behavior, we introduce a novel 'triple circle' methodology, with which we explicitly control for both selection of the social circle within the overall population and for the possibility of correlated, unobserved effects.[21] If unobserved heterogeneity is an important problem, then it should affect both the financial circle and the outer social circle. Thus, finding different results for the inner and the outer circles, conditioning on population behavior suggests that the difference is not due to unobserved heterogeneity, because such heterogeneity would necessarily have a significant effect on both circles. The empirically implemented specifications are:

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

and

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

We are able to control for a wide range of characteristics and attitudes of the household head, $\widetilde{\boldsymbol{\tau}}_i$. 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), a proxy for individual information (self-reported individual perception of the most recent realized stock market cumulative return), proxies for resources and constraints (educational attainment, employment status, assets, income, perceived borrowing constraints,

[21] Our 'triple-circle' methodology separately identifies the effects of the inner, the outer, and the population-minus-social circle outcomes and characteristics on individual behaviour. The necessity of this approach arises from our interest in peer behavior within a competitive market environment.

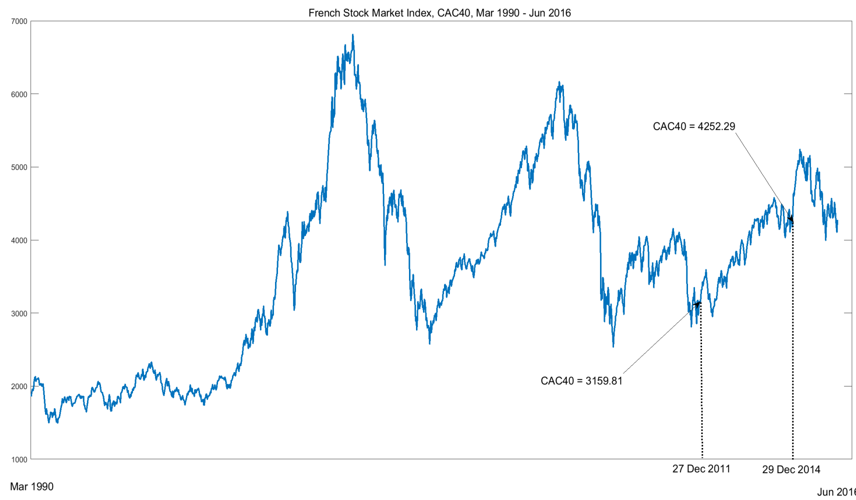


Figure 1: French stock market index, CAC 40, weekly data, 3 March 1990 - 27 June 2016. Source: Yahoo Finance.

and achieved liquid saving over the past year), and region of residence.[22] In all specifications, we also include dummies for item non-response and inconsistent responses, especially to the questions about perceived peer and population behavior.[23]

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

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

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

- 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 returns is equal to +1.6%. Positive deviations of perceptions from the low cross-sectional mean and optimism that is greater than the average observed among respondents of given characteristics in the sample seem consistent with the respondent having more informed perceptions and expectations more in line with available historical evidence.[24]

Table 2 reports estimates from these two specifications for subjective expected returns. The regression specification in column (1) includes, in addition to the usual household controls, respondent perceptions regarding how *informed* members of the two peer circles are. It can be seen that the share of the financial circle that the respondent regards as informed about the stock market is positively and significantly related to the respondent's subjective expectation of future return. The relationship is quantitatively significant: a one-standard-deviation increase of 17.2 percent in the mean share of a respondent's financial circle that is informed about the stock market increases the mean expected return by approximately +0.5 percentage points (or about a 30% increase relative to the unconditional mean expected return of +1.6 percentage points). By contrast, the corresponding share of the outer circle is found to be statistically insignificant. Similarly, for the share of the population informed. This difference in results suggests that the observed significant correlation is not simply due to unobserved heterogeneity and creates a presumption in favor of a causal effect from the financial circle that we will subject to further scrutiny below.

[24]Dimson, 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. times 5 years, or around 10% which is almost an order of magnitude larger than the cross-sectional mean expected return of 1.6%.

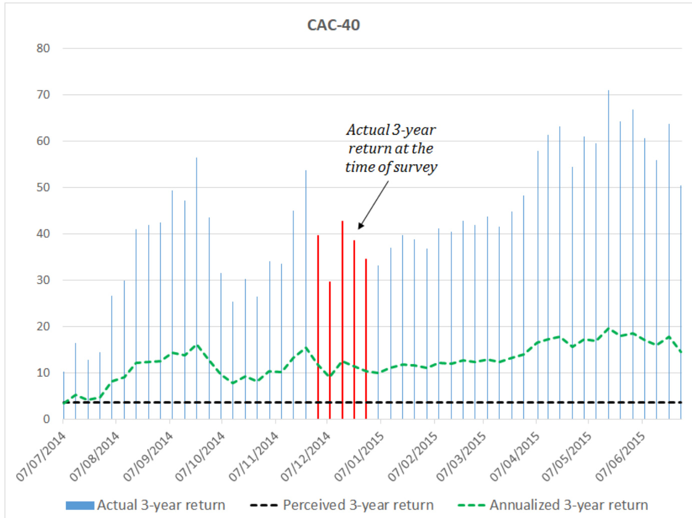


Figure 2: French stock market CAC 40, three-year stock market returns, weekly data, July 2014 to June 2015. The blue bars show cumulative 3-year returns and in particular, the red segment shows the actual cumulative 3-year return at the time that the survey was fielded, Dec 2014. The green dashed line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

The specification in column (2) focuses on the shares of the financial and of the outer circle that the respondent perceives as *participating* in the stock market. Again, we find that the share of stockholders in the financial circle has a positive, quantitatively and statistically significant effect on subjective expected stock market returns, while the corresponding share in the outer circle (or of the population) does not: a one standard deviation increase in the mean share of the respondent's financial circle that invests in the stock market increases the mean expected return by approximately +0.4 of a percentage point, representing about a 24% increase relative to the unconditional mean expected return.

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

In line with the recent literature on inflation expectations by households (Armentier et al., 2016) and firms (Coibion et al., 2018), columns (3) to (5) of Table 2 introduce subjective perceptions of recent stock price growth (over the past three years) in the regression of subjective stock market return expectations.[25] 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.[26] We focus on the mean of each respondent's subjective probability distribution over the size of the realized three-year stock market return. For brevity, we will be referring to this as the respondent's perceived return, with the previously introduced notation $Perc.R$. Consistent with results reported in the literature on inflation expectations, we find that perceived returns are strongly statistically significant in the subjective expectations regressions, controlling for respondent characteristics and perceptions about peer characteristics, regardless of whether peer variables are included in the regression or not. Strikingly, neither the share of informed peers nor the share of stockholders in the peer circle retain their statistical significance in the presence of subjective perceptions regarding the recent past return. This finding suggests that respondent perceptions regarding how informed their financial circle is or how extensively its members participate in the stock market influence subjective expectations of future returns only to the extent that they influence perceptions of recent past returns.

Next, we examine how perceived returns R_t^i are associated with perceptions about peer information, k_i^*, or group stockholding behavior, D_i^e, as follows:[27]

$$R_t^i = Perc.\ R = \eta_0 + \eta_{1,FC} k^*_{i,FC} + \eta_{1,OC} k^*_{i,OC} + \eta_{1,P} k^*_{i,Pop} + \mathbf{v}_i \boldsymbol{\eta} + \varrho_i, \qquad (15)$$

or

$$R_t^i = Perc.\ R = \eta_0 + \eta_{1,FC} D^e_{i,FC} + \eta_{1,OC} D^e_{i,OC} + \eta_{1,P} D^e_{i,Pop} + \mathbf{v}_i \boldsymbol{\eta} + \varrho_i, \qquad (16)$$

[25] Measuring individual information sets is difficult even in experimental settings, but some progress has been made by extending Manski's (2004) probabilistic elicitation techniques to facts (as opposed to events), as in Arrondel, Calvo-Pardo and Tas (2014), Afrouzi, Coibion, Gorodnichenko and Kumar (2016) and Coibion, Gorodnichenko and Kumar (2018).

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

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

where ϱ_i is an individual zero-mean error term distributed normally conditional on covariates, $\mathbf{v}_i$ is a vector of individual characteristics, including individual perceptions about the respondent's relative standing in terms of peer characteristics (professional status, education and total wealth), and we use the same symbols for coefficients only for economy of notation and not to indicate equality across specifications. We report estimates in columns (6) and (7) of Table 2. Interestingly, we find that perceived past returns are related to the perceived share of financial circle peers who are informed or who participate in the stock market, but not to the corresponding features of the outer circle. Quantitatively, a one standard deviation increase in the mean share of the respondent's financial circle informed increases the mean perceived return by around 1.0 percentage point, representing about a 27% increase relative to the unconditional mean. The respective numbers for participating in the stock market are 0.8 percentage points, representing approximately a 23% increase relative to the unconditional mean. This is consistent with our findings in the expectations regressions that did not control for perceived returns and with the introduction of such controls rendering the peer circles insignificant.

All in all, results in Table 2 paint a consistent picture: any influence of peers on subjective return expectations operates through altering perceptions of past returns. The finding that only the financial and not the outer social circle are related to perceptions of past returns also suggests that the observed relationship is unlikely to arise from unobserved heterogeneity, a conclusion that we will return to in what follows. The identified effects are conditional on relative standing measures of peer characteristics, none of which are statistically significant. This is consistent with the view that mindless imitation does not affect expectations of returns.

This first set of results is strongly consistent with the presence of an information channel in peer influences running only through the financial circle and only through perceptions of what happened in the recent past. It also points to a novel role for friends and acquaintances in enabling respondents to process factual information about past stock market outcomes beyond findings in the literature on the importance of own cognitive ability and financial knowledge for financial behavior.[28]

4.3. Stockholding. Our preceding analysis of subjective stock market expectations above has confirmed our model's prediction (common to models of Bayesian learning from peers) that connectedness to people more knowledgeable about the stock market receives a higher weight when forming expectations about stock market returns. In addition, more knowledgeable connections raise the reported mean

[28] See, for example, Christelis, Jappeli and Padula (2010), Grinblatt, Keloharju and Ikäheimo (2011) or Hurd, Van Rooij and Winter (2011).

expected return, bringing it closer to available long-run historical estimates (e.g. Dimson et al., 2008; Le-Bris and Hautcoeur, 2010). Since expected returns are positively related to desired portfolio exposure to stocks, this alone would suffice to create a role for social interactions in stockholding decisions. In this section, however, we examine our second prediction, i.e. whether social interactions and connectedness reduce the posterior variance of returns and thereby increase the prevalence of stockholding and the degree of exposure to stockholding risk, beyond its indirect effect through stock market expectations.

Our starting point is the demand for investing in the stock market in expressions (9) and (10). 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 (9) suggests the following econometric specification for agent i's share of financial wealth invested in the stock market:

$$D_i = \%FW_i = \max\{0,\ \lambda_0 + \underset{(+)}{\lambda_1 k_i^*} + \underset{(+)}{\lambda_2} Expec\ R_i + \underset{(-)}{\lambda_3} \rho_i + \boldsymbol{\tau}_i \boldsymbol{\lambda} + u_i\}, \qquad (17)$$

where u_i is an individual-specific error term. The vector $\boldsymbol{\tau}_i$ 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. It also includes individual perceptions about the respondent's relative standing in terms of peer characteristics for both the respondent's social (professional status) and financial circles (professional status, education and total wealth) to capture conformity-driven peer effects on financial behavior.[29] In addition, individual perceptions about population behavior/information are also included as observable controls for social circle selection effects, as well as for correlated effects due to aggregate events such as a 'news shock' or a 'market trend'. The signs under the constant coefficients indicate the theoretically predicted signs: more/better informed connections reduce the equilibrium posterior variance of expected returns (coefficient λ_1), a higher expected net excess return (coefficient λ_2) and lower risk aversion (coefficient λ_3) 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

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

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.[30] Note that, in both cases, portfolio demand, stock market expectations, and stock market perceptions play a potentially important role.

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

$$D_i = \%FW = \max\{0,\ \zeta_0 + \zeta_1 D_i^e + \underset{(+)}{\zeta_2} Expec\ R_i + \underset{(-)}{\zeta_3} \rho_i + \boldsymbol{\tau}_i \boldsymbol{\zeta} + w_i\}, \qquad (18)$$

where D_i^e represents a feature of the respondent's social circle, in this case the extent of peer participation in the stock market, as perceived by the respondent. In specification (17) we focus on respondents' perceptions about how informed their financial and outer circles are about the stock market; and in (18) we use their perceptions regarding stock market participation of the two circles, all of which are identified relative to the average population information about and participation in the stock market, as perceived by the individual.

Stock Market Participation. Column (1) of Table 3 presents results for a participation probit that employs responses on how informed the three circles are perceived to be. We confirm that subjective expected returns are positively and significantly related to participation, consistent with existing portfolio models, even after controlling for a number of household characteristics and for its declared willingness to take risks, formulated as absolute risk aversion. Interestingly, however, we find 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. This provides empirical support for our second prediction, i.e. that having more/better informed connections reduces the equilibrium posterior variance of stock returns. However this is not true for either the outer circle or the

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

population average information.

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

However, we also find that stock market participation among the outer circle has a positive and statistically significant relationship to the respondent's own decision to hold stocks relative to the perceived overall population participation rate. Further, from comparing both, 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. The finding that respondents are influenced by the participation of people in their social circle with whom they do not discuss financial matters indicates that a tendency for conformism and mindless imitation as regards stock market participation cannot be ruled out.

Columns (3) and (4) pursue further the econometric problem of potential unobserved heterogeneity creating the observed correlations. In both cases, it is possible that the observed relationships arise from unobserved factors that influence both the respondent and the respondent's peers. Splitting the social circle into financial and outer circles already provides evidence against unobserved heterogeneity, but now we have in column (2) a case in which we observe the joint significance of both circles. Although the population-wide effect is not statistically significant, in columns (3) and (4), we undertake a placebo test of the hypothesis that the statistical significance of the peer variables arises from a tendency for members of the same age and education group living in the same region to behave in the same way due to unobserved group factors. To this end, we reshuffle the responses regarding how informed the two circles are and how heavily they participate in the stock market, respectively. We find that, when each respondent is matched not with his or her own responses regarding the financial and outer circles, but with those of a random person in the same age and education group and living in the same area, the coefficients on both circles are no longer statistically significant. This supports the view that the observed correlations in columns (1) and (2) do not arise from unobserved group factors that affect all members of the same age and education group who reside in the same area, including the respondent.

Conditional portfolio shares. Columns (5) and (6) of Table 3 adopt a tobit specification in order to test for peer influences on the size of the exposure to stockholding risk in the portfolio, conditional on holding stocks. Symmetrically to columns (1) and (2), columns (5) and (6) examine the role of perceptions regarding how informed the two circles are and to what extent they participate in the stock market, relative to *perceptions* about the population. Here, the result is the same, regardless of which feature of the peer circle we consider: higher shares of informed or participating members of the financial circle are related to greater exposure to stockholding risk, providing support for the main theoretical prediction. But so does the share of the outer circle investing in the stockmarket, which now accounts for about a half of the overall peer effect on the share of wealth invested in the stockmarket: a 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. Just as above, we identify financial and outer circle peer effects of perceptions relative to how respondents perceive the overall population, as a guard against unobserved social group effects. Columns (7) and (8) support the argument that the effects identified on the intensive stockholding margin are not due to unobserved group heterogeneity, by repeating the analogue placebo counterfactual exercises as reported under columns (3) and (4) for the participation decision. We also note that the effects on the conditional share are net of the identified peer effects on subjective expectations.

All in all, the results in Table 4 suggest that exchange of useful information and possibly mindful imitation are strongly related to whether individuals participate in the stock market and to the share of financial wealth invested in the stock market, conditional on participating; yet, we also find some evidence of mindless imitation of the outer circle.

Robustness. So far, we have subjected our findings of a relationship between peer information/peer participation and respondent behavior to the scrutiny of distinguishing between the inner (financial) circle and the outer social circle, as well as of running placebo tests as ways to handle unobserved heterogeneity. In this section we provide some additional robustness checks in support of our findings.

First, we examine robustness of our results to recognizing that respondents have a choice of whether to form a financial circle or not, and that this choice may be taken jointly with the decision regarding stockholding. Specifically, it may be that people have some unobserved reason to hold stocks and this factor also pushes them to form a financial circle with whom they can discuss stockholding and other financial matters. This joint decision could induce the observed correlation between stockholding and financial sector attributes without any implication of causality from the financial circle to the respondent's stockholding behavior. To deal with this issue, we follow Blume et al. (2011) and we treat group choice and behavior (within a group) as a set of joint outcomes.[31] 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.[32] We estimate the following bivariate probit econometric specification:

$$\begin{cases} \Pr(Stocks_i > 0) = \Phi(\lambda_0 + \lambda_1 k^*_{iFC} + \lambda_2 k^*_{iOC} + \lambda_3 k^*_{iPop} + \lambda_4 Expec\ R_i + \lambda_5 \rho_i + \boldsymbol{\tau}_i \boldsymbol{\lambda}) \\ \Pr(FC_i > 0) = \Phi(\nu'_1 k^*_{iSC} + \nu'_2 k^*_{iPop} + \nu'_3 Expec\ R_i + \nu'_4 \rho_i + \boldsymbol{\tau}_i \boldsymbol{\nu}') \end{cases} \tag{19}$$

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

[31] The standard approach in the literature has been 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 Metropolitan Statistical Areas which define communities. Here, we take the view by Blume et al. (2011) according to which self-selection contains information about the respondent's preferences, "*which will depend on the social interactions that occur in groups over which he is choosing*". (p.880)

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

In principle the more being in the financial circle and discussing financial matters with the respondent has to do with exchanging information rather than engaging in mindless imitation, the more we would expect respondents to form a financial circle when they perceive a larger share of informed peers. Moreover, we would not expect this decision to be influenced by the share of people they perceive as candidates for imitation.

Table 4 presents four bivariate probits. Odd-numbered columns correspond to the stock market participation branches of the corresponding bivariate probits, while even-numbered columns are the branches depicting the choice of whether to form a financial circle or not. In regressions (1) and (3), the share of the social circle participating enters the regression for whether the respondent has a financial circle or not, while the share of the financial circle participating enters the second leg of the stock market participation decision. In regressions (2) and (4), the share of the social circle perceived to be informed about the stock market plays this role, with the corresponding share of the financial circle participating entering the stock market participation leg.

The stock market participation results under columns (1) and (3) confirm the results we obtained earlier, even when we now also allow for a unobserved correlation in the two decisions: subjective expected returns are positively correlated with stock market participation, and so are the perceived shares of informed members in the financial circle, as well as of the participating members in the financial or outer circles. The estimates for the corresponding second branches provide additional support for the presence of informative social interactions: the share of informed members of the social circle is statistically significant for the choice to form a financial circle, but the share of participating members is not.

Moreover, Table 4 sheds light on the main concern leading to the bivariate probit specification, namely that respondents who intend to invest in the stock market choose, within their social circles, the peers with whom to discuss their own financial matters. In that case, the error terms u_i and ν_{iFC} would be highly correlated such that $u_i = \phi\nu_{iFC} + \upsilon_i$, and the results reported in previous tables would be biased due to selection. The last three rows in Table 4 report such correlations ϕ and the Wald test statistics and associated p-values for different specifications of (19) considered, and in no case can we reject the null of independence, $H_0 : \phi = 0$. In addition, estimated coefficients on the peer variables and on other covariates under columns (1) and (3) tend to be similar to those in Table 3.

The robustness of our findings to explicit consideration of the joint decision to have a financial circle and to hold stocks may admit an intuitive interpretation, also in light of Blume et al. (2011, 2015): by conditioning on the share of peers informed or participating with whom the respondent does not exchange on own financial matters (i.e. on the outer social circle information or behavior), we are implicitly controlling for the possibility of selection into the financial circle in specifications considered in previous sections.[33]

Another possibility is that the information or behavior of those peers with whom the respondent does not exchange on her/his own financial decisions (outer circle) is measured with error. If that were the case, the results reported in Table 2 would be subject to attenuation bias and the effect of the participation or information of the outer circle on the individual's behavior would be biased towards zero. To account for this possibility, we exploit responses of individuals regarding population participation in and information about the stock market and treat them as an instrument. This is because these responses (i) can be excluded from the stockholding equations, since they are never statistically different from zero, conditional on covariates, and (ii) are reliable, e.g. for the average stock market participation rate in our sample of 21.7%, respondents do seem to have on average an accurate perception of 19.39% (see Table 7 of summary statistics). The results reported at the bottom of Table 5 under even-numbered columns confirm the latter, with 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.

Odd-numbered columns in Table 5 report results for stockholdings (columns 1 and 3) and the share of financial wealth conditional on positive stockholdings (columns 5 and 7), when information from or participation of the respondent's outer circle is allowed to be measured with error. 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 5 has associated p-values above 20% for all specifications, and thus we cannot reject the null of no measurement error. The estimated effects in Table 5 are about one order of magnitude larger than the non-instrumented ones (as reported in Table 2) and are only statistically significant for the participation and information from the respondents' financial circle; nevertheless, because our test indicates no measurement error, the preferred results are those reported in Table 2.

Finally, to account for the possibility of functional form misspecification error,

[33] This is supported by the results reported under columns (5) and (7) where the peer effects from the outer circle are mistakenly excluded, resulting in an increase in the correlation in the error terms of the group selection and the behavior within a group equations.

Table 6 reports the results of allowing for interaction terms between inner and outer circle peer effect behavior or information and expectations of returns, under columns 3 and 4 for stockholdings, and 7 and 8 for the conditional share, for our baseline econometric specifications (17) and (18). The interaction terms are never statistically different from zero, and therefore not reported, while the non-interacted estimated effects are qualitatively and quantitatively similar to the results in Table 2 (reported again for comparison in Table 6, under columns 1 and 2 for stockholdings, and under columns 5 and 6 for the conditional share). In fact, the results of the estimation with interaction terms provide additional support for the presence of the information channel, since one-standard-deviation increases in expectations (on stockholdings) are almost twice as big at the extensive margin (77% bigger) and about 25% larger at the intensive one, relative to the baseline results reported in Table 2.

All in all, allowing for functional form misspecification, measurement error and the possibility of selection provide useful robustness checks for our earlier findings and some additional support for the hypothesis that social interactions have a significant informative, rather than purely mindless imitation, content.

4.4. Comparison to experimental evidence. Banerjee et al. (2013) and Bursztyn et al. (2014) adopt experimental methods to disentangle information from imitation effects of the social circle. Banerjee et al. (2013) consider a novel microfinance program and replace the unconditional individual probability of participation by the individual probability of participation conditional on individual information sourced from friends. Once informed, they find that an agent's decision to participate in the program is not significantly influenced by the fraction of her friends participating, concluding that the influence of peer participation is mainly an information effect.[34] It is possible to construct an extreme interpretation of their findings that would be in conflict with ours. Under such an interpretation, if people are generally aware of the existence of stocks, they should no longer be influenced by the share of their peers participating in them. Such an interpretation would be in contrast to our findings.

We opt for a different interpretation, which stresses the nature of the underlying financial product. The particular microfinance product may have a much higher probability of participation conditional on awareness than stocks do. To take an extreme, if practically all people who know about the microfinance product choose to use it, the value of social links is in transmitting otherwise inaccessible information

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

and providing more information has no further effects. Yet we know that stock market participation is quite limited even among the many people aware of stocks in developed economies. Thus, there is room for further information beyond the existence of stocks to deliver effects on stock market participation and on the degree of exposure to stockholding risk.

Bursztyn et al. (2014) adopt a different experimental strategy and find empirical support for both information and imitation channels. They design a field experiment amongst socially paired investors of a Brazilian brokerage firm, and through sequential randomization, they separate the effect of a social peer actually purchasing a new financial product from being informed about it. This is accomplished by randomly informing peers about products, but also controlling whether they are able to invest in them or not. They are thus able to decompose the total effect of observing a peer hold a product into one that comes from the information that the peer is interested in having the product and one that comes from the information that the peer has been successful in acquiring the product. In this setup with fully controlled information flows, knowledge that a peer is interested in owning the new product is the only participation information that the respondent receives, and it can have a sizeable effect on the respondent's decision. It is entirely possible that observing peers participating in a mature and well-known product, such as stocks, will only have an incremental effect on the respondent's own decision. The objective to control the information flow restricts attention to unknown products with unknown appeal to others.

In our analysis, we deal with a well-known, yet information-intensive product in a developed economy, namely stocks in France. The more limited role for mindless imitation in the context of a widely known and mature product such as stocks is quite intuitive: not much information is added by learning that an extra person holds it, compared to learning this about a completely novel product.

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

5. Conclusions

We provide a model where purely informative social interactions influence subjective expectations of future stock market returns 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, collected in December 2014 and May 2015, we find strong support for the presence of informative social interactions, as well as some 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 perceptions of recent returns and only through them, expectations of future returns. Stock market participation and the degree of exposure to stocks, conditional on participation, are positively influenced by stock market expectations. However, this is not the only channel through which peers influence stockholding behavior. Even controlling for subjective mean 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. We did not find evidence that the corresponding attributes of the outer social circle influence perceptions of past stock returns or expectations of future returns. These findings are consistent with the notion that social interactions tend to be, at least in part, informative in relation to stockholding. However, we did find some evidence for the presence of imitation of stock market participation observed in the outer social circle. Unlike what happens with the financial circle, respondents do not discuss financial matters with members of this outer circle, and this creates a presumption for the presence of mindless imitation in the participation decision alongside informative social interactions.

We have followed a three-pronged approach to dealing with unobserved heterogeneity being the source of these results. First, we distinguish between attributes of the financial and of the outer circle: unobserved heterogeneity would tend to make both relevant rather than only one, as is observed in several of our results. Since those results are also conditional on corresponding population attributes, selection and correlated effects should also be less of a concern. Second, we perform placebo tests, where respondents' perceptions regarding the financial and the outer circle are reshuffled across respondents of the same age, education, and region of residence. We find that such reshuffling eliminates the estimated effects. Third, we adopt a bivariate probit specification which recognizes the possibly joint nature of the decision to hold stocks and to form a financial circle. When we treat group choice and behavior within a group as a set of joint outcomes, the null of independence among the two choices cannot be rejected in our sample, and our estimates tend to be similar regardless of whether we allow for a joint decision or consider stockholding choices separately. As a final robustness exercise, we use four questions from the TNS2015 questionnaire (questions C5, D6, D7 and D8) that ask respondents to report how they perceive themselves relative to those in their social and financial circles, in terms of professional standing, value of their financial assets and qualifications.[35] The reported empirical results are conditional on these social utility covariates, which are never statistically significant, providing further evidence against homophily driving our model-backed interpretation of the estimated information peer effects.

Informative social interactions imply a potentially powerful channel through which financial information and financial literacy can permeate through the economy, even if the original information or financial education content reaches a relatively small segment of the population. They point to a social multiplier in financial education or financial information even in countries with advanced financial development and in products that are mature and widely known, as is the case of stockholding in France. They provide a (partial or superior) substitute for financial advice, if ill-conceived, poorly incentivized, or hardly trusted. Finally, they are likely to grow in importance, as use of social media and the potential to reach more people with new information spread rapidly. Yet the data also indicate the presence of some mindless imitation in stockholding. This, along with the inequities involved in having access to less informed peers, 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 Expec-

[35] For all these questions, respondents answered that less than half of their acquaintances were similar to them in terms of assets, qualifications and/or professional standing. See Appendix C, Table 7.

tations, Information and Stock Market Participation: Evidence from France. Southampton Discussion Paper Series in Economics and Econometrics.

[4] Bilias, 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 WP22258.

[6] Banerjee, A., A.G. Chandrasekhar, E. Duflo and M. Jackson, 2013. The Diffusion of Microfinance. *Science* 341, 1236498.

[7] 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.

[8] 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.

[9] Blume, L. E., W. A. Brock, S. N. Durlauf and R. Jayaraman, 2015. Linear Social Interactions Models. *Journal of Political Economy* 123(2): 444–496.

[10] Bordalo, P., N. Gennaioli, Y. Ma and A. Shleifer. 2017. Overreaction in Macroeconomic Expectations. Working Paper, Bocconi University.

[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] Bursztyn, 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*, forthcoming.

[28] Fuster, A., R. Perez-Truglia, M. Wiederholt and B. Zafar. 2018. Expectations with Endogenous Information Acquisition: An Experimental Investigation. *Mimeograph.*

[29] Georgarakos, D., M. Haliassos, and G. Pasini, 2014. Household Debt and Social Interactions, *Review of Financial Studies*, 27(5), 1404–1433.

[30] Girshina, A., T.Y. Mathae and M. Ziegelmeyer, 2017. Peer effects in stock market participation: Evidence from immigration, *Mimeograph.*

[31] Giustinelli, P., and M. D. Shapiro. 2018. SeaTE: Subjective ex ante Treatment Effect of Health on Retirement. Ann Arbor, MI: University of Michigan Retirement Research Center (MRRC) Working Paper, WP 2018-382.

[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. Generalised 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 Neighbours. *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, 2018. Financial Literacy Externalities, *Review of Financial Studies,* forthcoming.

[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] Ozsoylev, H.N., Walden, J. , Deniz Yavuz, M., and R. Bildik, 2014. Investor Networks in the Stock Market. *Review of Financial Studies* 27(5): 1323–1366.

[56] Peress, J., 2004. Wealth, Information Acquisition and Portfolio Choice. *Review of Financial Studies* 17(3): 879–914.

[57] Sims, C., 2003. Implications of Rational Inattention. *Journal of Monetary Economics* 50(3): 665–690.

[58] 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+	Respondent's relative standing in terms of FC members' educational attainment	D7	TNS2015
SC Rel.Stand. Edu.+	Respondent's relative standing in terms of FC members' total wealth	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: Expectations and perceptions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
VARIABLES	Expec.R	Expec.R	Expec.R	Expec.R	Expec.R	Perc.R	Perc.R
%FC Inform.	0.0283**			0.0135		0.0554***	
	(0.0136)			(0.0135)		(0.0208)	
%OC Inform.	-0.00501			-0.0065		0.0088	
	(0.0269)			(0.0250)		(0.0384)	
%Pop. Inform.	-0.0039		-0.0043	-0.00177		-0.0009	
	(0.0188)		(0.0199)	(0.0182)		(0.0233)	
%FC Particip.		0.00236*			0.0102		0.0491**
		(0.0126)			(0.0124)		(0.0213)
%OC Particip.		0.00453			-0.0056		0.0494
		(0.0358)			(0.0347)		(0.0461)
%Pop. Particip.		-0.0014	0.0051		0.0027		-0.0066
		(0.0226)	(0.0251)		(0.0216)		(0.0265)
SC Rel.Stand. Prof.+	0.0115	0.0110	0.0043	0.0053	0.0055	0.0225	0.0194
	(0.0144)	(0.0144)	(0.0129)	(0.0128)	(0.0128)	(0.0209)	(0.0208)
SC Rel.Stand. Prof.-	0.0222	0.0230	0.0194	0.0177	0.0187	0.0227	0.0205
	(0.0150)	(0.0151)	(0.0143)	(0.0139)	(0.0140)	(0.0246)	(0.0245)
FC Rel.Stand. Prof.+	-0.0105	-0.00977	-0.0136	-0.0152	-0.0135	0.0231	0.0205
	(0.0123)	(0.0124)	(0.0118)	(0.0115)	(0.0115)	(0.0194)	(0.0196)
FC Rel.Stand. Prof.-	0.0009	0.00101	-0.0104	-0.0081	-0.0082	0.0364	0.0373*
	(0.0143)	(0.0143)	(0.0141)	(0.0137)	(0.0136)	(0.0254)	(0.0220)
FC Rel.Stand. Wealth+	0.196	0.224	0.208	0.227	0.250	-0.108	-0.0761
	(0.370)	(0.373)	(0.339)	(0.339)	(0.342)	(0.496)	(0.497)
FC Rel.Stand. Edu.+	0.0481	0.0531	0.0469	0.0502	0.0621	-0.0703	-0.100
	(0.350)	(0.349)	(0.334)	(0.333)	(0.333)	(0.490)	(0.486)
Perc. R			0.282***	0.282***	0.283***		
			(0.0265)	(0.0264)	(0.0264)		
Risk aversion	-0.0584	-0.0600	-0.0276	-0.0263	-0.0264	-0.152***	-0.158***
	(0.0393)	(0.0393)	(0.0350)	(0.0348)	(0.0349)	(0.0584)	(0.0582)
Constant	3.920*	3,756*	3,115	2.737	2.442	4.862	5.194*
	(2.147)	(2.162)	(1.960)	(1.945)	(1.951)	(3.117)	(3.128)
Controls	yes	yes	yes	yes	yes	yes	yes
Observations	2,535	2,535	2,535	2,535	2,535	2,328	2,328
F	2.325	2.3869	4.391	4.262	4.332	4.149	4.152
R^2	0.0457	0.0458	0.157	0.159	0.159	0.0975	0.0971

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

TABLE 3: Stockholdings

VARIABLES	(1) Pr(Stocks>0)	(2) Pr(Stocks>0)	(3) Pr(Stocks>0) placebo test	(4) Pr(Stocks>0) placebo test	(5) E(%FW>0)	(6) E(%FW>0)	(7) E(%FW>0) placebo test	(8) E(%FW>0) placebo test
%FC Inform.	0.00267***		0.00093		0.0289		0.0200	
	(0.000588)		(0.000666)		(0.0197)		(0,0210)	
%OC Inform.	0.000234		0.000922		0.0409		-0.0092	
	(0.00132)		(0.00120)		(0.0419)		(0.0372)	
%Pop. Inform.	-0.000528		8.78e-0.5		-0.037		-0.023	
	(0.00087)		(0.000893)		(0.0309)		(0.0249)	
%FC Particip.		0.00217***		0.000855		0.0325*		0.0169
		(0.000649)		(0.000696)		(0.0192)		(0.0209)
%OC Particip.		0.00246*		0.000694		0.0791**		-0.0358
		(0.00127)		(0.00129)		(0.0402)		(0.0401)
%Pop. Particip.		-0.000175		0.000697		-0.022		0.00274
		(0.00097)		(0.000937)		(0.0364)		(0.0277)
SC Rel.Stand. Prof.+	1.65e-06	-0.000132	4.15e-05	-3.64e-05	-0.0158	-0.0178	-0.0143	-0.0160
	(0.000712)	(0.000699)	(0.000728)	(0.000735)	(0.0266)	(0.0275)	(0.0232)	(0.0226)
SC Rel.Stand. Prof.-	-0.000216	2.63e-05	0.000173	0.000262	0.00610	0.0130	0.0067	0.0079
	(0.000771)	(0.000753)	(0.000787)	(0.000795)	(0.0242)	(0.0257)	(0.0238)	(0.0231)
FC Rel.Stand. Prof.+	0.000312	0.000235	0.000657	0.000665	0.0083	0.0032	0.0143	0.0124
	(0.00066)	(0.000649)	(0.000646)	(0.00066)	(0.0231)	(0.0239)	(0.0198)	(0.0193)
FC Rel.Stand. Prof.-	0.00015	0.00018	-0.000215	-0.000136	-0.0235	-0.0251	-0.0255	-0.0214
	(0.00084)	(0.000835)	(0.000819)	(0.000827)	(0.0257)	(0.0272)	(0.0244)	(0.0237)
FC Rel.Stand. Wealth+	-0.00110	0.00767	-0.00607	-0.00544	0.345	0.404	0.321	0.283
	(0.0190)	(0.0184)	(0.0182)	(0.0184)	(0.616)	(0.644)	(0.565)	(0.549)
FC Rel.Stand. Edu.+	0.00439	0.00526	0.00328	0.00420	0.856	0.879	0.579	0.591
	(0.0186)	(0.0182)	(0.0182)	(0.0184)	(0.635)	(0.665)	(0.569)	(0.554)
Expec. R	0.00201**	0.00195**	0.00224**	0.00223**	0.104***	0.106***	0.0975***	0.0931***
	(0.000958)	(0.000934)	(0.00102)	(0.00102)	(0.0352)	(0.0368)	(0.0329)	(0.0320)
Risk aversion	-0.00415**	-0.00396**	-0.00418**	-0.00403**	-0.108*	-0.107*	-0.0921*	-0.0840
	(0.00187)	(0.00180)	(0.00181)	(0.00183)	(0.0600)	(0.0634)	(0.0543)	(0.0529)
Controls	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	-1192	-1194	-1193	-1195	-3623	-3620	-3617	-3616
LR χ^2	445.0	434.6	492.3	489.7	398.7	403.3	399.7	402.5
Pseudo R^2	0.175	0.174	0.171	0.170	0.0521	0.0528	0.0524	0.0527

Notes: Marginal effects from probits of stock market participation (columns 1-4) and tobits of share of financial wealth invested in the stock market (direct or indirect), conditional on investing (columns 5-8), on share of financial and outer circles informed about or participating in the stock market . In all cases we control for household characteristics (age, gender, marital status, number of children, education, region of residence, employment status, liquidity and/or borrowing constrained and quartiles for total wealth, income, savings), item non-responses (NR), and item 'don't know' (DK). Inconsistent answers (IC) are included if due to 'rounding' and discarded otherwise. Marginal effects are calculated excluding NR, DK and IC observations. Robust standard errors are reported in parentheses, and statistical significance at the 10, 5, and 1 percent levels is indicated by *, **, and ***, respectively. Source: Author computations using data from merged TNS2014 and TNS2015 surveys in France.

TABLE 4: Bivariate probits

VARIABLES	(1) Pr(Stocks>0)	(2) Pr(FC>0)	(3) Pr(Stocks>0)	(4) Pr(FC>0)	(5) Pr(Stocks>0)	(6) Pr(FC>0)	(7) Pr(Stocks>0)	(8) Pr(FC>0)
%FC Inform.	0.00260***				0.00253***			
	(0.000606)				(0.000567)			
%OC Inform.	0.000390							
	(0.00131)							
%SC Inform.		0.00340**		0.00335**		0.00343**		0.00337**
		(0.00150)		(0.00148)		(0.00150)		(0.00149)
%Pop. Inform.	-0.000495	-0.00148		-0.00146	-0.000405	-0.00149		-0.00147
	(0.000871)	(0.00114)		(0.00112)	(0.000850)	(0.00114)		(0.00113)
%FC Particip.			0.00222***				0.00279***	
			(0.000666)				(0.000605)	
%OC Particip.			0.00263**					
			(0.00129)					
%SC Particip.		-0.000711		-0.000677		-0.000745		-0.000713
		(0.00151)		(0.00149)		(0.00152)		(0.00150)
%Pop. Particip.		-0.000125	-0.000262	-0.000122		-0.000119	0.000185	-0.000113
		(0.00130)	(0.000968)	(0.00128)		(0.00131)	(0.00097)	(0.00129)
SC Rel.Stand. Prof.+	-0.000396	0.000121	-0.000494	0.000118	-0.000428	0.000123	-0.000444	0.00012
	(0.000729)	(0.00066)	(0.000720)	(0.000652)	(0.000743)	(0.000663)	(0.000742)	(0.000655)
SC Rel.Stand. Prof.-	-0.000203	0.000624	9.29e-05	0.000617	-0.000201	0.000626	-6.11e-05	0.000620
	(0.000779)	(0.000769)	(0.000762)	(0.000760)	(0.000798)	(0.000773)	(0.000793)	(0.000764)
FC Rel.Stand. Prof.+	n/s		n/s		n/s		n/s	
FC Rel.Stand. Prof.-	n/s		n/s		n/s		n/s	
FC Rel.Stand. Wealth+	n/s		n/s		n/s		n/s	
FC Rel.Stand. Edu.+	n/s		n/s		n/s		n/s	
Expec.R	0.00242**	0.000337	0.00231**	0.000332	0.00253**	0.000340	0.00247**	0.000336
	(0.00120)	(0.00110)	(0.00117)	(0.00109)	(0.00122)	(0.00111)	(0.00122)	(0.00110)
Risk Aversion	-0.00419*	-0.00426*	-0.00391*	-0.00421*	-0.00435*	-0.00429*	-0.00403*	-0.00424*
	(0.00232)	(0.00242)	(0.00222)	(0.00239)	(0.00239)	(0.00244)	(0.00232)	(0.00241)
Controls	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) stock market participation (odd numbered columns) and (ii) formation of financial circle (even numbered columns). In all cases we control for household characteristics (age, gender, marital status, number of children, education, region of residence, employment status, liquidity and/or borrowing constrained and quartiles for total wealth, income, savings), item non-responses (NR), and item 'don't know' (DK). Inconsistent answers (IC) are included if due to 'rounding' and discarded otherwise. Marginal effects are calculated excluding NR, DK and IC observations. Robust standard errors reported in parentheses. Statistical significance at the 10, 5, and 1 percent levels is indicated by *, **, and ***, respectively. Source: Author computations from merged TNS2014 and TNS2015 waves in France.

TABLE 5: Measurement Error

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 Partici first stage
%FC Inform.	0.0112***	0.188***			0.0701*	0.192***		
	(0.00366)	(0.0099)			(0.0406)	(0.0099)		
%OC Inform.	-0.0103	-			-0.172	-		
	(0.0150)				(0.162)			
%FC Particip.			0.00846*	0.216***			0.0621	0.219***
			(0.00504)	(0.0093)			(0.0506)	(0.0097)
%OC Particip.			0.00381	-			-0.0564	-
			(0.0199)				(0.207)	
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. Prof.+	n/s	n/s	n/s	0.023**	n/s	n/s	n/s	0.017*
FC Rel.Stand. Prof.-	n/s	n/s	n/s	n/s	n/s	n/s	n/s	0.026**
FC Rel.Stand. Wealth+	n/s	n/s	n/s	n/s	n/s	n/s	n/s	n/s
FC Rel.Stand. Edu.+	n/s	n/s	n/s	n/s	n/s	n/s	n/s	n/s
Expec.R	0.00727**	-0.00268	0.00734**	0.00198	0.106***	-0.00311	0.109***	0.00337
	(0.00317)	(0.0144)	(0.00316)	(0.0134)	(0.0357)	(0.0154)	(0.0364)	(0.0150)
Risk Aversion	-0.0142**	0.00762	-0.0138**	0.0146	-0.114*	-0.0059	-0.110*	0.0072
	(0.00633)	(0.02873)	(0.00626)	(0.02776)	(0.0607)	(0.02973)	(0.0626)	(0.0290)
%Pop. Inform.	-	0.187***		-	-	0.184***		-
		(0.0127)				(0.0133)		
%Pop. Particip.		-	-	0.164***		-	-	0.167***
				(0.0142)				(0.0150)
Controls	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 behaviour 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 behaviour instrumented by population information and behaviour 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. In all cases we control for household characteristics (age, gender, marital status, number of children, education, region of residence, employment status, liquidity and/or borrowing constrained and quartiles for total wealth, income, savings), item non-responses (NR), and item 'don't know' (DK). Inconsistent answers (IC) are included if due to 'rounding' and discarded otherwise. Marginal effects are calculated excluding NR, DK and IC observations. Robust standard errors reported in parentheses. Statistical significance at the 10, 5, and 1 percent levels is indicated by *, **, and ***, respectively. Source: Author computations from merged TNS2014 and TNS2015 waves in France.

Table 6: Interaction Effects on Stockholding

VARIABLES	(1) Pr(Stocks>0)	(2) Pr(Stocks>0)	(3) Pr(Stocks>0) interacted	(4) Pr(Stocks>0) interacted	(5) E(%FW>0)	(6) E(%FW>0)	(7) E(%FW>0) interacted	(8) E(%FW>0) interacted
%FC Inform.	0.00267***		0.00262***		0.0289		0.0304	
	(0.000588)		(0.000595)		(0.0197)		(0,0194)	
%OC Inform.	0.000234		0.000155		0.0409		0.0304	
	(0.00132)		(0.00132)		(0.0419)		(0.0403)	
%Pop. Inform.	-0.000528		-0.000522		-0.037		-0.0403	
	(0.00087)		(0.000866)		(0.0309)		(0.0309)	
%FC Particip.		0.00217***		0.00211***		0.0325*		0.0334*
		(0.000649)		(0.000662)		(0.0192)		(0.0187)
%OC Particip.		0.00246*		0.00251*		0.0791**		0.0692*
		(0.00127)		(0.00128)		(0.0402)		(0.0398)
%Pop. Particip.		-0.000175		-0.000188		-0.022		-0.0248
		(0.00097)		(0.000970)		(0.0364)		(0.0365)
SC Rel.Stand. Prof.+	n/s	n/s	n/s	n/s	n/s	n/s	n/s	n/s
SC Rel.Stand. Prof.-	n/s	n/s	n/s	n/s	n/s	n/s	n/s	n/s
FC Rel.Stand. Prof.+	n/s	n/s	n/s	n/s	n/s	n/s	n/s	n/s
FC Rel.Stand. Prof.-	n/s	n/s	n/s	n/s	n/s	n/s	n/s	n/s
FC Rel.Stand. Wealth+	n/s	n/s	n/s	n/s	n/s	n/s	n/s	n/s
FC Rel.Stand. Edu.+	n/s	n/s	n/s	n/s	n/s	n/s	n/s	n/s
Expec. R	0.00201**	0.00195**	0.00349**	0.00280**	0.104***	0.106***	0.184***	0.0931***
	(0.000958)	(0.000934)	(0.00169)	(0.00138)	(0.0352)	(0.0368)	(0.0509)	(0.0320)
Risk aversion	-0.00415**	-0.00396**	-0.00418**	-0.00398**	-0.108*	-0.107*	-0.106*	-0.0840
	(0.00187)	(0.00180)	(0.00187)	(0.00180)	(0.0600)	(0.0634)	(0.0598)	(0.0529)
Controls	yes	yes	yes	yes	yes	yes	yes	yes
Observations	2,525	2,525	2,525	2,525	2,294	2,294	2,294	2,294
Log-likelihood	-1192	-1194	-1191	-1193	-3623	-3620	-3620	-3619
LR χ^2	445.0	434.6	445.6	437.2	398.7	403.3	403.4	406.1
Pseudo R^2	0.175	0.174	0.176	0.175	0.0521	0.0528	0.0528	0.0531

Notes: The table reports marginal and conditional marginal effects for the probability of stock market participation (columns 1-4) and the share of financial wealth invested in the stock market conditional on participating (columns 5-8) when inner and outer circle peer information are interacted with subjective expectations of returns (columns 3-4 and 7-8 respectively). Results under columns 1-2 and 5-6 report for ease of comparison the results under the same columns in Table 2, when no interactions are allowed. In all cases we control for household characteristics (age, gender, marital status, number of children, education, region of residence, employment status, liquidity and/or borrowing constrained and quartiles for total wealth, income, savings), item non-responses (NR), and item 'don't know' (DK). Inconsistent answers (IC) are included if due to 'rounding' and discarded otherwise. Marginal effects are calculated excluding NR, DK and IC observations. Robust standard errors are reported in parentheses, and statistical significance at the 10, 5, and 1 percent levels is indicated by *, **, and ***, respectively. Source: Author computations using data from merged TNS2014 and TNS2015 surveys in France.

TABLE 7: Summary statistics

	Patrimoine INSEE 2014-15	TNS 2014 & 2015 merged				
VARIABLES	Mean	Mean	St.Dev.	Min.	Max.	Observations
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 7: Summary statistics (*continued*)

	Patrimoine INSEE 2014-15	TNS 2014 & 2015 merged				
VARIABLES	Mean	Mean	St.Dev.	Min.	Max.	Observations
(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.

APPENDICES, FOR ONLINE PUBLICATION

A. Noisy Rational Expectations Equilibrium

We conjecture that the risky asset price has the form

$$p = \pi_0 + \sum_{j=1}^{n} \pi_j x_j - \gamma Z_n, \tag{20}$$

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 $\mathbf{S} \equiv Cov\,(R\boldsymbol{\epsilon}) = R\Sigma R^T$,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, $K = diag\,[k_1, ..., k_n]$, 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.

$$\lim_{n\to\infty} \frac{\|W\|_\infty}{n} = 0 \tag{21}$$

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

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

A4. The limit

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

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

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

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

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

where

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

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

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

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

1. Conjecture a functional (linear) form for the price, with unknown coefficients.
2. Derive beliefs for the agents as a function of the price coefficients (using Bayesian updating).
3. Derive the optimal demands for the agents given their endogenous beliefs.
4. Impose market clearing and solve for the stock price.
5. Impose rational expectations (i.e. equalize coefficients) and confirm that the corresponding system of equation generates a solution, which will then provide solutions for the price coefficients.

6. Check, with asymptotic arguments that conditions required to ensure that the coefficients exist (i.e. the system has solution) as $n \to \infty$, are satisfied given the assumptions A1-A4.

The detailed steps of the proof are available upon request.

B. Definitions of Variables

Table 7 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, $p^i_{t+1,k}$, of each of the seven alternative scenarios, $k = 1, ..., 7$. Each scenario represents a possible outcome range for the index percentage change between t and $t+5$, $R_{t+1}(5) \equiv \frac{P_{t+5}}{P_t} - 1$.[36] Questions C40 and C41 provide subjective upper and lower bounds for the percentage change, $R^i_{\max}$ and $R^i_{\min}$ respectively. The corresponding outcome ranges are:

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

and respondents' subjective likelihoods are accordingly:

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

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

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

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

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

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

See Campbell et al. (1997) for details.

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%

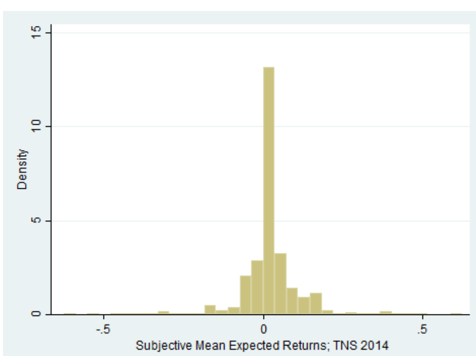
... has decreased by more than 25%

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

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

Three years prior to the time when the survey was conducted (December 2011), the stock market index was only slightly above the floors reached after the dot-com and Lehman Brothers busts. But, between late December 2011 (CAC 40 = 3159.81) and late December 2014 (CAC 40 = 4252.29), the index had increased an overall 34.57%. Figure 1 in the main text shows the time window chosen within the wanderings of the CAC-40 index between 1990 and 2016. Table 5 reports summary sample statistics for respondents' answers regarding perceptions and beliefs about stock market returns, imposing a uniform distribution within the different outcome ranges. A striking finding is that households are on average also pessimistic regarding the most recently realized three-year cumulative stock market return (Dec. 2011-Dec. 2014). Although this might be due to imperfect 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.



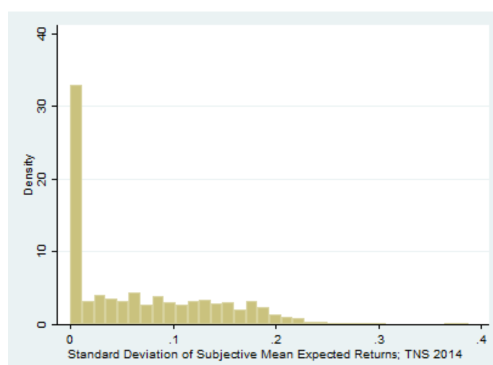
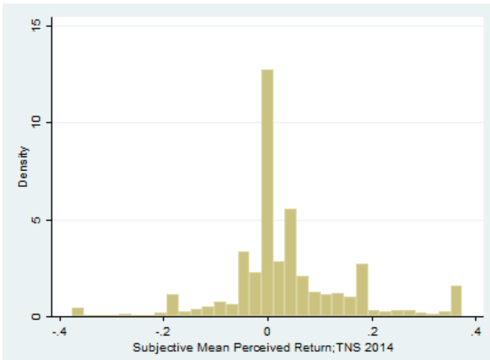


Figure B1a:

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



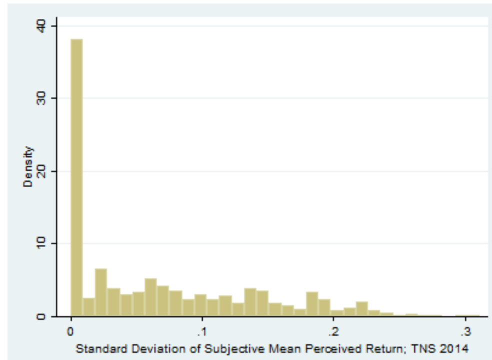


Figure B1b:
Histograms of the subjective mean (left panel) perceived three-year cumulative realized return, and its standard deviation (right panel); TNS2014.

Arrondel et al. (2014) report that categorical answers to frequency, variety and access specialized media, advice from professionals, as well as the number of stock market transactions carried over the last year, increase the likelihood of being factually informed. Interestingly, parents' stock ownership status ('cultural transmission'), parents' educational attainment or family background do not increase the odds of being factually informed, and actually significantly decreases them for those who follow family advice. Since those who follow friends' advice are more likely to be informed, they interpret the evidence as being consistent with social interactions being instrumental in gathering information (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 Bilias, 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 5.

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 5. 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 5.

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 5.

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):[37] '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'.

[37] If we were interested in a continuous measure, we would implement the method of simulated residuals (Gourieroux et al. 1987). We would then regress an ordered probit of the respondents' total wealth (bracket) on demographic and socio-economic household characteristics. Once we would have the estimated total wealth, a normally distributed error would be added. We would then check if the value falls inside the bracket originally chosen by the individual. If not, another normal error would be added and so on until we the true interval is correctly predicted. Doing so would allow us to overcome the non-response problem for some households. Would there be a missing value, the predicted value plus a normal error would be directly used.

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

Income: For the income of the household, the survey (question A12) asks the respondent which of the nine predefined available brackets better corresponds to her situation: 'Less than 8,000', 'between 8,000 and 11,999', 'between 12,000 and 15,999', 'between 16,000 and 19,999', 'between 20,000 and 29,999', 'between 30,000 and 39,999', 'between 40,000 and 59,999', '60,000 or more' and 'No income'. Income refers to the respondent's annual income (earnings, pensions, bonuses, etc.) in Euros, net of social contributions but before personal income taxes.[38] In addition, TNS reports also the net gross monthly income of the household, in Euros. From the empirical distribution, we obtain the income quartiles the bounds of which are given by '11,999', '19,999' and '29,999'. The reference category is the first quartile, 'less than 11,999'.

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

Preferences.

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

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

[38] When the survey took place, income in France was not taxed at the source.

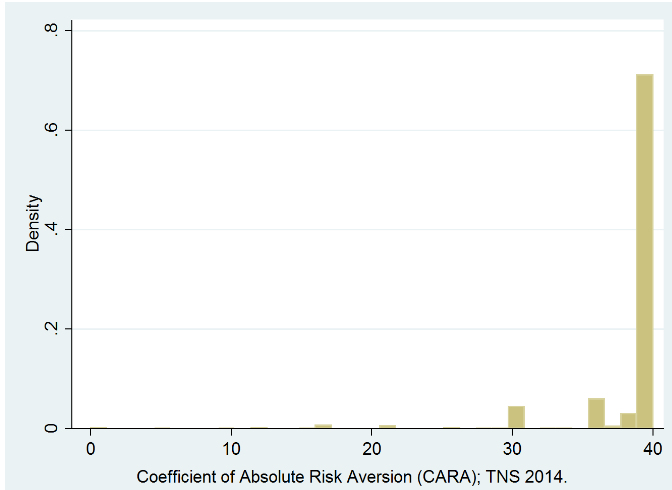


Figure 3: Histogram of responses to the hypothetical lottery that enables elicitation of the respondent's coefficient of absolute risk aversion (CARA) -TNS 2014 survey question C44.

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. 3 displays the histogram of responses, which is very skewed to the left but remains within the range responses found in the literature. Further details regarding the measure of absolute risk aversion can be found in Guiso and Paiella's (2008) work.

Demographics.

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

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

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

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

Constraints.

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

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

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

Information.

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