Sociability and Stock Market Participation: a Test for Alternative Transmission Channels

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Abstract

Models accounting for social interactions have recently attracted the attention of several economists who consider market interactions being insufficient to explain some economic outcomes. At the same time, two theories suggest that participation to certain investments can theoretically be affected by peer choices: the first is based on the desire to imitate his own peers, while the second hinges on the learning arising from observing his peers. An assessment on the superiority of one theory over the other represents a valuable policy statement, since public intervention should markedly differ depending on which transmission mechanism is prevailing. In this paper, I test whether one of these theories should prevail on the other in explaining stock market participation of Italian households and find out that dynamic learning dominates the rival conformist theory. Robustness of the results can be claimed with respect to the grouping criterion.

JEL Classification: *D1, D8*
Keywords: Participation to stock markets; Peer groups; Non-nested binary models.

1 Introduction

Usually, in the economic analysis, interactions among individuals take place indirectly through the markets and this working line rules out the possibility of accounting for several determinants of individuals' behaviour which are not formally modelled into a market environment. Indeed, agents operating in the market are thought to be mutually conditioned by the interactions of their own expectations, preferences and constraints and these cross agents relations have been theoretically modelled by Pollak (1976) who explicitly introduces interdependency in the preference structure. Although several empirical works concerning demand systems with social interactions flourished by this approach, in the more recent years, the literature has been focused on the role of social interactions in determining individual outcomes. Even if such a reasoning should pervade the whole microeconomics, at the moment, it is applied mainly to investigate investors' behaviour in financial markets, outlining the relevance of custom, conformity, fashion and imitation for explaining both aggregate and individual behaviour in the markets. In particular, the impact on financial markets of the aforementioned elements is broadly acknowledged and stressed by several authors (among others, Bikchandani, Hirshleifer and Welch,1992).

One of the most striking puzzle in the field of financial economics is the limited participation of households to stock markets and, in general, to financial markets. Ideally, according to the early models of wealth allocation, each agent should hold a positive fraction in all the available assets in order to either achieve a full diversification of his own portfolio or maximize his own utility, whereas, empirically, a large fraction of household recording zero holding for stocks can be observed. With the path-breaking contribution due to Haliassos and Bertaut (1995), *inertial* factors such as culture, trust in financial institutions, conformity have been placed aside to *fundamentals* (wealth, age, risk profile, etc.) for shedding some light on the determinants of household participation to stock markets. In principle, household wealth echoes on both investor risk aversion and importance of fixed costs mainly based on participation fees and monitoring costs (Vissing-Jorgensen, 2000). With respect to investor risk aversion, in the more common preference specifications, it is inversely related to wealth and, in turn, it reflects on greater propensity to enter financial markets as well as education, by leading to understand financial markets and decrease monitoring costs, increases the probability of entering stock market. According to the life-cycle hypothesis (Modigliani and Brumberg, 1954) even the age affects decisions concerning participation to financial markets; in particular, as the life-time horizon shortens, the probability of entering financial markets decreases as well.

Besides acknowledging these issues as major determinants of stock market participation, in the more recent years, many authors emphasize the relevance of other variables such as social variables or other determinants usually overlooked in economics. In particular, Guiso, Sapienza and Zingales (2005) highlight that investor trust in financial markets could represent the key for interpreting household participation to stock markets, whereas Hong, Kubik and Stein (2003) hinge the participation rate of U.S. households on social interactions, since financial information sharing can increase the equity culture and ignite a desire of imitating by other individuals. Moreover, with regard to the mechanism through whom stock market participation catches on, the authors sketch out two potential transmission channels: the first is related to the so called word-of-mouth, or observational learning (among others, Banerjee, 1992) , while the second hinges on the enjoyment coming out from discussing with peers on upward or downward movements of stock market indexes in the same fashion proposed by Becker (1991).

In this paper, once recognizing the relevance of social interactions for the Italian case (Guiso, Haliassos and Jappelli, 2002), I attempt to discern between observational learning and enjoyment from talking about the market on the basis of the data of Bank of Italy's Survey on Household Income and Wealth (SHIW). In models addressed to explain limited participation in stock market, sociability can be embodied in two different ways. The first relies on deriving some proxies for household sociability and using them as explanatories of market participation, while the second, inheriting some statistical mechanics tools, aims at capturing the interactions among households by modelling the similarity/dissimilarity of household endogenous choices on market participation. In other terms, while the first strategy is based on the possibility of carrying out from survey data some measure of sociability, the second models social interaction by inferring conformity in the economic outcomes of household decision problem. Basically, I adopt the second modelling strategy, since it allows discriminating between the different interaction mechanisms here investigated. Indeed, by making use of different specifications for the social utility component (Brock and Durlauf, 2001) corresponding to different interaction channels, I can provide some insights on the prevalence of one of the mentioned theories. However, since the Bank of Italy's survey is lacking in providing information on peer groups, I should compensate for by grouping households according to sensible criterion. In this context, I make use of the notion of social distance due to Akerlof (1997) which, along with geographical issues, allows explaining different investment patterns. Therefore, variables representing household sociability are treated as exogenous in forming group membership of Italian households.

Beyond contributing to the debate on equity premium puzzle (Mehra and Prescott, 1985) and on the effectiveness of policies aiming at tackling the lack of *equity culture* which also depends on the strength of social interactions, the ability in discerning which transmission channel prevails is crucial for several issues mainly linked to infer the dynamic of stock market participation. Indeed, in the word-of-mouth case, the outgo from the market due to poor performances should not generate negative externalities since the investors are thought having knowledge on the market behaviour, whereas negative externalities arise from the second transmission channel in which the outflow of one may represent the cause of the outflow of his peers as well. Therefore, leaving unchanged the fundamentals, an increase in stock market participation as a consequence of policies addressed to enlarge the *equity culture* occurs only when the transmission channel is based on observational learning. Conversely, in the enjoyment from talking about the market regime, the outcomes of these policies have to be considered intimately dependent on the contingent movement of stock market indexes. In other words, subsidizing programs aiming at spreading *equity culture* makes sense only if the underlying interactions take place through observational learning.

This paper is organized as follows. In section 2, I will refer to the theoretical underpinnings of the model and introduce the binary choice model with social interactions. In section 3, I present the results of a simulation based on interactions outlined in section 2. In section 4, I will discuss the empirical issues of the model with regard to the data and identification and testing issues. In section 5, I will outline the econometric results of the models and check for the consistency of the approaches one another, whereas, section 6 concludes.

2 Theoretical Background and Modeling Strategy

Theoretically, in the most of portfolio models, it is assessed that household have to hold stocks in order to maximize their own utility and the fraction invested into this asset should be driven by risk aversion and stock return volatility (Merton, 1973). However, such a parsimonious explanation of household stockholding is violated by empirical evidences which show that determinants of household participation to financial markets should be related to a bulk of sociodemographic variables embracing wealth, age, education, race, etc.. Due to the large mixture of motives driving participation choice, several authors (among others, Hong, Stein and Kubik, 2003) successfully point out the relevance of social interactions in upward shifting the stock market participation rate of U.S. households, even controlling for the usual determinants of market participation. In principle, there are several reasons that can be called for defending the introduction of sociability in the set of the explanatories for stock market participation; indeed, such arguments crucially depend on the typology of interaction that one should consider. The most important for the purpose of this paper is the *preference interaction* (Manski, 2000) arising from the circumstances in which individual utility functions embody arguments depending on other individuals' expected choices. Such a representation is consistent with the settings I will model in the remainder of this section. In particular, since investors may have pleasure from discussing on stock market patterns as well as on movies, books, sport teams (Becker, 1991), the expected participation of peer group components and the word-of-mouth communications of investment plans followed by other individuals may reduce the participation costs, especially those related to the household's familiarity with the market (Huberman, 2001). Indeed, both the desire to conform their peers' choices and the learning arising from comparing market experiences can lead to a sensible reduction of the factors which can block the market access. In order to include this working line in household participation to stock market, I present the theoretical framework based on the works due to Hong, Stein and Kubik (2003) and Brock and Durlauf (2001).

Suppose an investor facing with the standard problem of selecting the optimal weights to be invested into stocks and riskless bonds. The rate of return entailed by stocks is a random variable, whereas that of bonds is constant and known by the investor. In a rational environment, household chooses the weight invested into stocks in order to maximize the utility of expected value of end-period wealth. Hong, Stein and Kubik (2001) show that households termed as socials, *i.e.* those who socially interact with peer households, present a different participation condition with respect to those termed as non-socials. In particular, households are observed to enter stock market only if the certainty-equivalent gain from participating is greater than a fixed participation cost which, for the sole social household, is decreased by the presence of an interaction factor increasing in the number of peer households entering financial markets. Hence, the model predicts *ex ante* higher participation for social than non-social households. By making use of econometric framework proposed by Brock and Durlauf (2001), I obtain a testable representation for this model. Consider a generic household, I say i, who in each period should decide whether participate or does not to stock market. The participation choice is hence modelled by a binary variable ω whose value equals 1 whenever household i takes part in stock market and 0 otherwise. Since household behaves in a maximizing fashion, ω is the solution of the following maximization program:

$$\omega_i = \max V\left[\omega_i, X_i, G_k, E\left(\omega_{-i}\right)\right]$$

where $V(\ldots)$ is a generic pay-off function which is assumed to be invariant across individuals. The choice on whether household i enter or does not stock markets is related to four different arguments: the choice itself, X_i which includes household specific information, G_k containing features related to the peer group associated with household i and $E\left(\omega_{-i}\right)$ being the term through which the interaction among households takes place. More specifically, the decision concerning on taking part in the stock market depends also on the expectations on the participation of other households belonging to the peer group k.

Since a specialization of this generic pay-off function is essential to achieve a functional form that can be suitable for testing the implications of the model and, at the same time, analytically tractable, I follow Durlauf (2001) and assume that V is additively separable in three components:

$$V\left[\omega_i, X_i, G_k, E\left(\omega_{-i}\right)\right] = u\left(\omega_i, X_i, G_k\right) + s\left[\omega_i, X_i, G_k, E\left(\omega_{-i}\right)\right] + \epsilon_i\left(\omega_i\right) \quad (1)$$

in which u, s and ϵ_i represent private deterministic utility, social deterministic utility and private random utility, respectively. The last component allows capturing unobservable elements affecting the participation choice such as the idiosyncratic participation cost (Hong, Stein and Kubik, 2001), the individual talent in managing risky investments or the individual trust in stock markets (Guiso, Sapienza and Zingales, 2005). The difference between private and social deterministic utility functions is worth deepening.

The rationale of this approach is that choice concerning ω_i does not present only an intrinsic economic value, but it is also undertaken by taking into account additional sources of utility arising from the discrepancy between the individual's and his peers' choices: indeed, individuals may need to (do not) conform with the choice of those who they need to (do not) imitate. This standpoint coherently falls into line with the views expressed in several studies in which the extrinsic role played by stock market participation is stressed.

One of the more challenging issues of this methodology is the specification of the social utility function s. Several specifications for s have been proposed differing from interaction complexity that modeler should capture and, therefore, this task underlies the knowledge of the existing interactions among households. As discussed by Hong, Stein and Kubik (2001), among the several interaction theories which one can state, two are the most promising in explaining household participation to financial markets: *i)* the word-of-mouth (or observational learning); and *ii)* enjoyment from talking about the market (hereafter, it will be also called conformist model). In the first, individuals learn one another about asset features, trading strategies and pay-off granted by each financial instrument (Bikchandani, Hirshleifer and Welch, 1992). In this work, being interested in spillover effects, I neglect the fact that learning may concern different sides of stock market. In the second, individuals get pleasure in talking about their own market experiences and, in turn, financial issues are conversation arguments as well as sports, books, movies, etc. (Becker, 1991). According to this theory, household stock ownership is driven by fashion, *i.e.* the desire of mutually conforming behaviour; in particular, some households may be induced to hold stocks by the need of imitating their own peers in order to do not be excluded from the group.

Since the most of available surveys does contain any information on neither household sociability nor peers, I will make use of different specifications for social utility component in order to distinguish different behaviours. Even if participation to stock market may socially be driven by a combination of these theories, I model them as mutually exclusive[1]. More specifically, I model the enjoyment from talking about market by the most general specification termed as *weighted interactions* and expressed as follows:

$$s\left[\omega_i, X_i, G_k, E\left(\omega_{-i}\right)\right] = -\sum_{\substack{j=1 \\ j\neq i}}^{n-1} \frac{J_{ij}}{2}\left[\omega_i - E_i\left(\omega_j\right)\right]^2 \tag{2}$$

in which J_{ij} is a set of weights relating participation choice of household i to those of other households belonging to a peer group and $E_i\left(\omega_j\right)$ denotes the expectation of household i on the participation choice of other households. Although this specification results to be very attractive due to its own generality, in empirical applications, one should impose some parametric restrictions on J_{ij} and on the expectation shaping mechanism in order to achieve the model tractability. This specification encompasses the need of conforming behaviour to that of peers, since it penalizes the deviation from the actions undertaken by group membership. Hence, it generalizes the conformist model due to Akerlof (1997) and, in this context, it is used as specification for the mechanism described by Becker (1991) since it measure the inclination to conform his own behaviour to the expected behaviours of his peers in order to being socially accepted in the group.

A second different specification termed by Brock and Durlauf (2001) as *dynamic learning* is quite similar to that presented in equation 2. It consists in replacing the expectations on the others' choices with choices undertaken in previous periods; in other terms, it can be formulated as below:

[1]In section 6, I will point out the plausibility of this modeling choice, at least from a statistical standpoint.

$$s\left[\omega_i, X_i, G_k, E\left(\omega_{-i}\right)\right] = -\sum_{\substack{j=1 \\ j\neq i}}^{n-1} \frac{J_{ij}}{2}\left[\omega_i - \omega_{j,-1}\right]^2 \tag{3}$$

in which $\omega_{j,-1}$ represents the choices of other households in previous periods. Even if this specification is affected by similar empirical pitfalls which need to be solved through parametric restrictions, it allows esteeming whether households should learn from the decisions taken by other household in previous periods. Also in this setting, individuals are penalized if they do not follow the choice undertaken by their peers in previous periods; in other terms, one learns from the others' decisions and, in turn, opts for entering financial markets.

With regard to the proposed specifications, three remarks are in order. Firstly, both the specifications are related to the information disclosure of household accounts: they should not be apt to share with peers information concerning the status of their personal finance. Therefore, the learning coming out from the observation of peers' choices is hardly undermined by the lack of disclosure, whereas the enjoyment from talking about the market seems to be less affected by this fact. However, it is straightforward that both channels fully operate among social households, whereas their working power can be drastically limited among non-socials. Secondly, in this setting, I deal with local interactions *i.e.* interactions among individual belonging to the same group which is traced by social and geographical criteria. The guidelines for delimiting household groups are discussed in the next sections: here, it is enough to remind that significant geographical patterns have been found in investigating stock market participation. Thirdly, the specification of observational learning mechanism exploits the intuition that learning is viewed as a temporally delayed behaviour, *i.e.* individuals observe, spend some time to learn and, finally, undertake the choice, whereas, disregarding issues inhibiting the choice[2], conformity entails that individual observe and simply undertake a mimicking choice.

The last assumptions I have to impose to close the model concerns the distribution of private random utility (ϵ_i) which will be relevant in the empirical part of this paper. The choice regarding distribution of private random utility presents benefits from both analytical and empirical standpoints. In particular, if I assume ϵ_i being normally distributed, the resulting statistical model is a standard probit.

In the next section, before moving to empirical issues, I will carry out a simulation which aims at clarifying the role of social interactions in affecting the individual deciding process.

[2] In this case, these issues may unlikely lie on unavailability of stocks to be bought or lack of stockbrocker to undertake the purchase, while other household specific features potentially inhibiting the entry into stock market will be controlled for in the empirical part.

3 The Qualitative Predictions of the Model

In this section, before presenting the empirical evidences concerning social interactions in Italy, I assess the theoretical predictions coming out from the model outlined above and I show that outcomes of models accounting for social interactions may strongly differ from those which do not consider inter-individual relations. In this context, one may refer to different models depending on the interaction typologies and such a choice theoretically affects the equilibrium; in particular, two options are allowed: a *stigma model* in which each agent undertakes his choice in a status-seeking perspective and a *conformist model* in which each individual behaves in order to obtain a position as closer as possible to those of his own peers (Akerlof, 1997). In the analysis of household participation to stock market, I focus on the second interaction typology (conformist model) since it is more suitable to investigate the impact of social interactions on the investment choices. Indeed, especially for transmission channel based on the enjoyment coming from talking about financial markets, a desire to conform to the investment choice of the peers may arise, whereas, in the observational learning, participation to stock markets takes place as a consequence of learning from peers' investment strategies. In this stage, no mentions concerning the prevailing vehicle for social interactions have been done, since I am mainly interested in showing different outcomes coming out from accounting for social interactions.

With regard to the model equilibrium, two results are worth being enunciated in advance: first, the existence of social interactions among individuals may prevent the attainment of socially desirable equilibrium, *i.e.* the one arising without social interactions[3]; second, this model, along with the embedded interactions, may result into a low level trap, *i.e.* the case in which stable groups often choose low levels of the choice variable since the desire to conform to their peers is dominant over the intrinsic value of the economic choice. In other words, for households surrounded by peers who do not enter stock market, the desire to imitate their peers overwhelms the intrinsic value of participation to financial market and leads to do not invest, *i.e.* to lower participation rates. Conversely, those households who interact with peers participating financial markets are much more motivated to invest by both intrinsic reasons and conformist desire. In both the cases, the outlined effects are magnified by household sociability.

In obtaining qualitative predictions from the model, I should specify a function describing the intrinsic value of the choice as well as a way to characterize the strength of the interactions. With regard to the equation 1, I should assign a specific functional form to $u(\omega_i, X_i, G_k)$ which represent the intrinsic value of choosing ω_i. Following Akerlof (1997), in order to preserve the analytical tractability, u is specified as a quadratic form of ω_i. Moreover, for sake of simplicity, I omit the exogenous variables (X_i, G_k) from u. Hence, u will be specified as follows:

[3] The equilibrium arising without social interactions is termed as socially desirable since it is established by taking into account the sole intrinsic determinants of the choice variable.

$$u(\omega) = \omega^{'} A\omega + b\omega \tag{4}$$

in which ω is a $n \times 1$ column vector containing the binary choice for each individual[4], A is a $(n \times n)$ diagonal matrix and b is a conformable vector. In order to evaluate the impact of social interactions on participation choice, the social utility component s has to be specified. From a general standpoint, I model the social utility function as below:

$$s(\omega) = g(\omega - \overline{\omega})^{'} D(\omega - \overline{\omega}) \tag{5}$$

in which, differently from the terms appeared in equation 4, $\overline{\omega}$ represents the average choices of a group of peers and D is a conformable symmetric matrix whose elements determine the weights of cross-individual interactions. Moreover, differences in setting $\overline{\omega}$ and D entail different interaction width: if the average choice is computed on the basis of the choices of all the agents populating the economy (and consequently, D is set according to this modeling choice), global interaction is considered, while, if such quantities are assessed with respect to the choice of a subset of individuals, who, according to spatial proximity notion, can be regarded as peers, then local interaction arises and, lastly, if the notion of spatial proximity is suppressed, but interactions are still involving a subset of individuals randomly selected, then random interactions take place. Finally, g represents the constant weight which each individual associates with the social utility function. As I will show in the remainder of this section, it plays a crucial role in determining household choices.

Equation 5 can be further manipulated as follows:

$$s(\omega) = -\omega^{'} T^{'} DT\omega$$

in which $T = \left[I - (n)^{-1} O\right]$ with I, n and O representing the identity matrix, the agents cardinality and a square matrix whose elements equal one, respectively. Hence, mimicking equation 1, I obtain the following expression:

$$V(\omega) = \omega^{'} \left[A - T^{'} DT\right] \omega + b\omega \tag{6}$$

An assessment on the stochastic term ε is neglected, since I focus mainly on the relevance of social interaction for the individual choice. Nevertheless, recent works on stock market participation stress the role of ε in terms of familiarity (Huberman, 2001) or trusting stock market (Guiso et al., 2005)[5].

The maximization of the latter expression entails to solve the so-called *Mixed Integer Quadratic Problem* (MIQP) which differs from standard optimization

[4] Due to the choice structures, ω should contain 1 if the corresponding agent does enter stock market and 0 otherwise.

[5] Despite I avoid considering stochastic component ε, individual randomness is ensured by randomly assigning the parameters of private utility function. Even under random parameterizations, the private utility function does not violate the usual properties: $u^{'}(x) > 0$ and $u^{''}(x) < 0$.

problems, i.e. those involving continuous variables, because of the presence of binary decision variables.

The presence of a social utility function may prevent the achievement of individual optimum defined as that which can be reached by evaluating the only intrinsic value of the choice. In particular, by running the optimization in unsociable environment ($g = 0$), I obtain that, regardless of the starting distribution of individual choices, *i.e.* even in the worst-case scenario in which initially nobody participates to financial markets, and independently from the individual risk tolerance, *i.e.* disregarding the values of the parameters in the private utility function, agents decide entering financial markets at the end of the optimization program.

Even if theoretically three interaction typologies may be considered, for sake of brevity, I focus on *random interactions* in which relations among different agents occur randomly and, in turn, independently from any notion of nearness[6]. This clear-cutting choice is due to a couple of reasons: *i)* several results arising from random interaction model are very close to those obtained from *global interaction* model; *ii)* results concerning *local interaction* model can be carried out by locally replicating global interactions.

In graph 1, participation choice is considered a function of both risk tolerance and expected peer choices. The stems denoting individual choice of entering stock market spring up in areas in which high levels of risk tolerance are recorded and peers are expected to participate[7]. Moreover, two issues are worth noticing: firstly, the role of expected peer choices is diminishing as the risk tolerance increases and, secondly, once individuals ascertain the participation of their peers, *i.e.* in the portion of horizontal plan where expected peer choices is greater than 0.5, the risk tolerance is the main driving factor for participation pattern. Similar arguments may be developed with respect to the number of contacts (see graph 2).

Investigating the determinants leading the participation choice, a crucial role is played by relationship between private and social utility: even disregarding the starting distribution of participants and non-participants to financial markets, the inclination of households to enter financial markets is intimately related to the prevalence of the private over social utility in the value function of the problem. In other words, as pointed out by Brock and Durlauf (2001), if the contribution of private utility to the value function overwhelms that offered by the social component, agents are rather willing to enter financial markets and, if the social utility prevails over the private utility, the *vice versa* holds. In graph 3, individual participation choice (black dots) and the evolution across individuals of the ratio between private and social utility (solid black line) are represented. Participation choices (dots with ordinates equaling one) correspond to those individuals whose private utility dominates the social component.

[6] Other interaction typologies may be termed as *global interaction* in which each agent populating the system interacts with all the others and *local interaction* in which interactions with a subset of individuals take place according to a closeness criterion.

[7] In this setting, I assume that one household expects her peers entering financial market if the peer expected choice is greater than 0.5.

In the next section, I will enrich the framework by accounting for household-specific features. These allow stochastically investigating the participation choice and, mainly, discriminating the channel through whom interactions take place.

4 The Empirical Issues

Having provided some theoretical evidences on the impact of social interaction on individuals' choices, in this section I deal with the empirical features of this topic. For sake of clarity, I distinguish two different issues which are the objects of the next subsections: *i)* the descriptive evidences arising from the dataset I am going to employ; *ii)* the issues related to identification and testing strategy used to discern between transmission channels through which social interactions are supposed to affect participation decisions. In the first stage, since the available data are lacking of information concerning whether households attend their neighbours, I mainly focus my attention on the possibility of delineating household groups, whereas in the second I face with the identification problems which can potentially arise from endogenous interaction models and the econometric tools which are essential to test for non-nested rival specifications.

4.1 Data and Descriptive Evidences

One of the more challenging issues given by this kind of empirical works is to find out the grouping criteria; in other words, the detection of a principle linking different individuals is imperative to measure the social utility component and the conformity in the individual choices. In practice, constructing a social network is an hard task, since only few data sources allow discovering individual peers and group membership with *ad hoc* questions, whereas, more frequently, researchers can only deduce social networks from exogenous features of each individual. The last approach is dominant in dealing with longitudinal data which, according to a certain sample scheme, aim at replicating the features of the underlying population; in fact, if the main instance driving the data collection is the reproduction of characters of a benchmark population, it is very rare, or virtually impossible, to find in the sample households who are members of a same social network. This paper is based on the Bank of Italy's Survey on Household Income and Wealth (2004). Biannually, the Bank of Italy carries out a survey by interviewing a sample of households and recording several demographic, economic and social features for each involved household. In the wave I am considering in this work, the interviewed households amount to $8,012$. Apart from being the most recent survey on Italian household financial accounts, this wave records the current household stock ownership and lifetime household stock ownership which will be crucial in the econometric analysis and, moreover, it provides measures of the time spent to monitor investment and the degree of risk aversion. However, since the sample involved in this survey should mimic the features of the whole Italian population, it does not offer any insight concerning neither relationships among sampled households nor their degree of sociability. Indeed, although in the Second Round of the Survey[8] political interests, affiliations to cultural, church, sporting, environmental protection, recreation associations jointly with participation to their meetings are recorded (see questions *R2.1* and *R2.2),* the resulting variables can be marginally used to infer on household sociability and, in general, the lack of more direct measures of sociability prevents from slavishly replicating the analysis in the fashion of Hong, Stein and Kubik (2001). Nevertheless, the variables mentioned up to this point do not carry enough information to evaluate household sociability. In other terms, although households can be defined as socials, from these data I cannot gather anything which can provide deeper characterization of household behaviour. In fact, the most of works dealing with social interactions makes use of data concerning friendship or membership of group that households haunt. Therefore, analyses based on the detection of peer groups has been released with regard to problem-specific databases such as data concerning college student performances in which peer group memberships are implicitly drawn or to more aggregated datasets necessitating of some preliminary work to design the social networks (Conley and Topa, 2002). In the latter way of detecting peer groups, one should hinge his\her own analysis on sensible assumptions intimately related to the data at hand: in particular, Borjas (1991) presumes that persons interact with members of their own ethnic group, Glaser et al. (1996) propose a geographical interaction way in which physical distance plays the major role, whereas Conley and Topa (2002) outline interactions driven by physical, ethnical and occupational distances.

In this paper, since evidences for Italy highlight that stock market participation patterns hardly differ across regions, the basic aggregating criterion should be the region in which households live. However, since the sole regional criterion seems to be lacking in capturing the notion of social distance due to Akerlof (1997), I also propose three refined grouping criteria by including another geographical criterion (the dimension of the dwelling town), a stratification by age classes and by income quartiles. With regard of the memberships defined by such criteria, I compute the peers expected choice; since the grouping criteria mostly form large clusters, the way I use to compute expectations is consistent. In table 1, I show that grouping criterion leading to the highest correlation between social utility component and participation choice is the one defined by regional and income quartile memberships, even if all the proposed criteria exhibit 1% statistically significant correlations.

Several recent works addressed to assess differences in stock market participation rate make use of specific variables approximating the level of social capital stimulating household participation to financial markets; traditionally, such differences are investigated at a regional level (Guiso, Haliassos and Jappelli, 2002). In this paper, the outlined approach is totally embodied since variables concerning group (regional) specific features enters the model through

[8] The Second Round is a subsection of the survey addressed to record some specific issues, in this case those related to *Opinions regarding Public Spirit and Taxation.* For quickness instances, it is addressed to a random subsample of households initially involved into the interviews.

the private utility function in which group specific variables are specified as arguments along with household specific characteristics. Indeed, I use regional data from the Italian central statistics institute (*ISTAT*) in order to capture the sociability of the environment that each household faces with. In particular, at a regional level, *ISTAT* carries out some indicators concerning the percentages of individuals who watch television, listen radio, read books and newspapers, use internet and personal computer, play sports, do voluntary work, pay funds to associations, attend the church and the number of banks and post offices for each hundred of inhabitants (see Table 2 for more details). Such a modelling choice is coherent with the presumption that households interact one another at a territorial level without any further insight concerning more sophisticated social relationship based on class of age, type of employment, etc. and stresses the wisdom that household sociability does not depend on household features *per se*, but it has also to account for the liveliness of the surrounding areas. Even in practice, the assessment that social capital (measured by variables regionally recorded) is embodied in the approach I am pursuing in this paper can be totally accepted, since proxies for social capital are significantly correlated with the peer expected participation choice, independently from the grouping metric[9].

4.2 Identification and Testing Strategy

In this section, I deal with some empirical features which have to be treated before showing the econometric results. These relevant issues regard the model identification, which probably represents the main difficult arising from endogenous interaction models and the testing tools which are much more specialized than those usually employed, since two non-nested rival models will be compared.

Several authors (among others, Manski, 2000) find in the difficulties arising from model identification the reason for the few empirical applications exploiting endogenous interaction models. Indeed, the coexistence of three effects (endogenous, contextual and correlated) simultaneously exerting their own effects on the set of parameters prevents from reaching a full interpretability of estimates[10]: this drawback is usually termed *reflection problem* (Manski, 2000). The reflection problem does not allow distinguishing whether the individual behaviour affects the mean group behaviour or, conversely, the mean group behaviour affects the individual choice. In a recent work due to Brock and Durlauf (2001), general necessary or sufficient conditions for the identification are provided; these are suitable, at least, from a theoretical standpoint, but further explorations should be necessary to clarify their implications for empirical applications. However,

[9] A table containing pairwise correlations between proxies of social capital and peer expected participation choice can be obtained from the author upon request.

[10] In this setting, endogenous effect takes place if household choices of entering financial markets are affected by the mean choice of their peers, contextual effects refer to the influence exterted by socioeconomic features of group membership on the participation choices and correlated effects relate the similarity in the choices of individuals belonging to the similarity in the backgrounds they are experiencing.

several empirical studies attempt to find out short cuts for model identification. In this bulk, it is possible to discern two different approaches: the first focus on some arguments which are addressed to assess the lack of one of the aforementioned effects and appear to be sensible in some specific circumstances, whereas the second is based on the sample selection model in which the outcome is corrected for the participation choice and, in turn, correlated effect is captured. Furthermore, a very recent work (Krauth, 2006) points out that identification of correlated effects may be achieved by sophisticating the estimation procedure through simulated maximum likelihood estimators.

In this paper, I underpin the identification strategy on two arguments. Firstly, the amplitude of the group formed by grouping criteria entails that usual econometric techniques can be applied (Brock and Durlauf, 2001) and, secondly, it is reasonable that household participation choice does not individually affect the mean participation choice, but inversely the mean group participation choice aggregately affect the individual choice. In other words, the largeness of defined groups allows me treating the behaviours of peers as exogenous to one's own behaviour and such a modelling choice appears to be sensible if one supposes that a single household cannot affect the decisions of households from her own group, whereas the mean choice of relevant peer group exerts a strong influence on her choice.

The second econometric issue arising from this work is to compare two non-nested competing models. Indeed, usual econometric tools provide with an ample variety of tests addressed to the comparison of nested specifications, *i.e.* those obtained by excluding one or several variables from unrestricted models. In this context, however, I need comparing two specifications which do not encompass one another. In fact, equation 1 takes on two different functional forms depending on the specifications (see equation 2 or 3) adopted to model the social utility component, $s\left[\omega_i, X_i, G_k, E\left(\omega_{-i}\right)\right]$.

Therefore, depending on the functional form of the social utility component, the equations which will be estimated are clearly non-nested[11], since one cannot be obtained by imposing linear restrictions over the parameters of the other and, hence, the usual econometric tests cannot be applied for establishing the superiority of a model over the other in approximating the true underlying stochastic process. In the practice, in order for facing with such a complication, two tests have been developed: the Vuong test (1989) and the distribution-free test (Clarke, 2003) which I am going to sketch out in the sequel.

Both the testing procedures hinge on the Kullback-Leibler Information Criterion (Kullback and Leibler, 1951) which entails that one model should be preferred to another if the individual contributions to the model log-likelihood are statistically larger than the individual contributions to log-likelihood of the alternative model. Taking this general principle as guideline, Vuong proposes to test the null hypothesis that the two competing models are equally close to the true specification; in formulae, I have that:

[11] Practically, equation resulting from conformist model will account for a mean computed on contemporaneous peer choice, while the one arising from dynamic learning will consider a mean of lagged participation choices of peers.

$$H_0 : E\left[L_n^a\left(\widehat{\beta}^a\right) - L_n^b\left(\widehat{\beta}^b\right)\right] = 0$$

where $L_n^a\left(\widehat{\beta}^a\right)$ and $L_n^b\left(\widehat{\beta}^b\right)$ are the log-likelihoods of the models labelled as a and b, respectively. Dividing the expression into brackets by its variance $\left(\sigma^2_{(L^a - L^b)}\right)$, Vuong carries out:

$$H_0 : \frac{L_n^a\left(\widehat{\beta}^a\right) - L_n^b\left(\widehat{\beta}^b\right)}{\sqrt{n}\sigma_{(L^a - L^b)}} \xrightarrow{d} N(0,1) \tag{7}$$

Equation 7 represents the Vuong statistic[12] which allows discriminating between two non-nested rival models and should be corrected for the model degrees of freedom if the numbers of covariates included into the models differ one another. Finally, it is worth remarking that normality arises only asymptotically.

A second testing procedure lies on the distribution-free test due to Clarke (2003). In order to compute this statistic, one should consider the vectors of individual likelihood for both the models and compute:

$$Z_i = L_i^a\left(\widehat{\beta}^a\right) - L_i^b\left(\widehat{\beta}^b\right)$$

From the vector Z_i, Clarke obtains a new vector of zeros and ones according to the following rule:

$$\Psi_i = \begin{cases} 1 & if \quad Z_i > 0 \\ 0 & if \quad Z_i < 0 \end{cases} \tag{8}$$

and, the distribution-free statistic equals to:

$$DF = \sum_{i=1}^{n} \Psi_i \sim Bin(n, 0.5) \tag{9}$$

Concerning the Clarke test, it is worth outlining three desirable features. Firstly, the distribution-free test does not necessitate calling for asymptotic theory, *i.e.* it is an exact test; secondly (and consequently), it outperforms the Vuong test in dealing with small samples; thirdly, it outperforms the Vuong test even when the correct discrimination is less likely to occur (low signal extraction).

Once equipped with these tools, in the next two sections, I will outline the model specifications under conformism and dynamic learning and, afterwards, comment the econometric results along with the outcome of the testing procedures to discriminate between the two transmission mechanisms which several authors have theorized.

[12] For the properties of this statistic, see the referenced article (Vuong, 1989).

5 The Model Specifications

In this section, I briefly clarify the model specification under both conformist and dynamic learning interactions with particular regard to the arguments to be included into the private utility function $u(\omega_i, X_i, G_k)$. This depends on both household specific features (X_i) pertinent to the economic, social and demographic spheres and group specific features (G_k) which are intended to approximate the effects coming from the socioeconomic environment experienced by the individual. Concerning this last point, two remarks are in order. First, since the individual outcome refers to the choice of entering financial markets, one may include indicators for the degree of financial coverage such as the number of banks\post offices for a hundred of inhabitants. Secondly, due to the broad notion of social capital and its relevance in determining household participation to financial markets (Guiso and Jappelli, 2005), one should also include some variables approximating this notion. Amongst the several variables which can be called for measuring social capital, in this context I opt for the number of individuals (for each number of inhabitants) paying funds to cultural associations (excluding sporting clubs). Although these can capture only some sides of social capital, here they are intended to measure the intensity of social interactions.

On the side of the household specific features, the task is relatively simpler due to the large mass of works investigating this topic and, hence, I specify the estimating equation by including the age and her own quadratic effect, the household savings, the sex of household head, the number of household components, the schooling degree and the employment status. Each variable aims at capturing effects whose relevance in determining household participation to stock market has been already stressed in earlier works.

For sake of easing the comparison between the desire of socially conforming and dynamic learning interactions, I do not modify the household specific and group specific sets of covariates. Indeed, there is not any theoretical *a priori* to claim that structural variables affecting stock market participation decisions differ under rival transmission channels. Due to this modeling choice, the competing specifications will differ only in the term arising from the social utility component which will be:

$$\overline{s}_{ig_k} = \begin{cases} \frac{1}{n_{g_k}} \sum_{j \in g_k} \omega_{jt} & under \quad conformism \\ \frac{1}{n_{g_k}} \sum_{j \in g_k} \omega_{jt-1} & under \quad dynamic\ learning \end{cases}$$

in which g_k and n_{g_k} denote the k-th cluster defined by any grouping criterion and the number of households belonging to it, respectively.

In the next section, I outline the econometric results carried out from the specifications discussed in this section.

6 Results

This section is devoted to show and, afterward, comment the econometric results with regard to their implication for the policy makers. In table 3, I show the estimates for the probit model whose specification guidelines have been outlined in the last section. In this table social interactions are captured within groups formed by applying the regional and class of age criteria. However, the probit estimates obtained from different grouping metrics do not markedly differ one another and the resulting peer interactions appear being informative in determining household participation to stock market.

Almost all the estimated parameters display a 1%-statistical significance and present signs supporting the theoretical *a priori*. In this context, a couple of evidences is worth being remarked. Firstly, as displayed in table 4, the test for the exclusion of social interactions from both the models is markedly rejected; in other words, according to several already referenced works, social interactions matter for the choice of investing in stocks. Secondly, although the strength of the parameters associated with social interaction may be partially due to the identification strategy, they exhibit a strong incentive to conform to their peers independently from the transmission mechanism. This commitment to conform may be the potential explanation for the lower participation to stock market recorded in Italian regions, especially the Southern part of Italy and the Isles. In particular, since households are affected by a strong incentive to conform and households entering stock market are relatively rare, one of the reasons excluding households from financial market can be the desire of emulating peers who systematically avoid participating to the stock market. This explanation can be helpful in rationalizing the empirical evidence testifying the coexistence of time-persistent subgroups who permanently stay out from financial markets and, at the same time, it can be theoretically reconciled with the *low-level trap* (Akerlof, 1997).

In table 5, the statistics to discern between conformist model and dynamic learning are shown with respect to all the grouping criteria. The statistical outcome seems being favourable to the dynamic learning theory. Indeed, both statistical procedures provide evidences in this direction. In fact, with the exclusion of the result arising under the only regional grouping criterion, the Vuong tests highlight a prevalence of dynamic learning over conformist theory. If the evidences arising from the Vuong statistics are considered too weak, the exact nonparametric Clarke test backs up dynamic learning theory[13]. In this case, the statistical outcomes are more clear-cutting than those arising from the Vuong tests and allow assessing the dominance of dynamic learning on the conformist theory. Hence, dynamic learning transmission channel seems to better rationalize the participation choices of Italian households than the conformist version of social interactions. Such a discrimination should provide some policy im-

[13] Indeed, in the second and fourth columns of Table 5, the Vuong tests display weak evidences in favour of dynamic learning, whereas in the first column, it cannot discern between conformist and dynamic learning models. Hence, the conclusion achieved through distribution-free test will be extremely precious.

plications. With regard to the behaviour of household participating financial markets, one may exclude that participation rate should vary over the time as a function of investors' sentiment. In other terms, this outcome should be plausible under conformist model, in which the enjoyment coming from talking on market performances should be understandably vanishing when the market bearishes and, in turn, households are led to suddenly quit the market. On the other side, the main implication of the dynamic learning lies on a different household behaviour consisting in progressively accumulating knowledge from observing their peer lagged choices and attempting to mimic the successful investment strategies. Such a desire to conform driven by increasing knowledge of financial markets entails much more balanced reactions even to a bearishing market. Moreover, in order to increase household participation to financial markets, public interventions aiming at spreading financial information should be boosted even by dynamic learning which can support their effectiveness.

Finally, in table 6, I display the estimates of a probit model in which the dependent binary variable is the one created in Clarke test (see equation 8). By the mean of the ancillary variable (Ψ_i), I can gather information on which household behaves according to dynamic learning or, alternatively, conformist model and, therefore, I can infer on the determinants of different behaviours. In this stage, it is worth remarking that, since vector Ψ contains only one element equaling zero, the modeling choice which regards to the rival transmission channels as mutually exclusive seems to be correct. In order to check the significance of some variables capturing the degree of financial information of each household, I am enforced to restrict the sample, since these variables are recorded only for a random subsample of Italian households. The striking evidence arising from table 8 is that opting for dynamic learning is not statistically affected by economic factors such as savings and labour income quartiles, but it is intimately related to sociodemographic (age, dwelling place, employment status), contextual (the degrees of penetration of both banks and cultural associations) and financial information variables (dynamism of personal portfolio management).

7 Concluding Remarks

Household participation to financial markets represents a crucial issue for both economic theory and policy interventions in practice. From the former standpoint, Vissing-Jorgensen (2002) claims that equity premium puzzle (Mehra and Prescott, 1985) can be solved by accounting for limited participation to financial markets, whereas, from the latter point of view, public interventions aiming at tackling the lack of *equity culture* necessitate a sound framework to assess the effectiveness across households. Since the path-breaking work due to Haliassos and Bertaut (1995), the role played by *inertial* factors such as trust in institutions, the desire to conform to their peers, etc. has been acknowledged. Therefore, in order to explain the stark differences highlighted by regional stock market participation rates, some authors (among others, Guiso and Jappelli, 2005) have stressed the role of social capital interpreted as the mass of individual relationships that may theoretically spread household participation to stock market. More recently, Hong, Kubik and Stein (2002) have shown that more social households much more likely enter stock market and have outlined two potential theories rationalizing such empirical evidence. In the same fashion proposed by Becker (1991), one may argue that, since stock markets may be a conversational argument such as sports, films, books and holidays, individuals need holding stocks in order to enjoy conversation with peers. On the other side, households may be driven to enter financial markets because they learn investment strategies and other relevant information from their peers and this fact plays a great part in lowering cognitive entry barriers. Discriminating between these two alternative theories can be valuable since they entail different behaviours and stability of participation rate to stock markets.

In this paper, I hinge on the interaction-based models due to Brock and Durlauf (2001) in order to test whether dynamic learning prevails over conformist model or *vice versa*. In this setting, several problems due to parameter identification arise and formally prevent researchers from distinguishing endogenous from correlated effects. Since the lack of variables outlining social networks do not allow defining capillary peer groups, I am enforced to cluster individuals according to socioeconomic distance in the fashion originally proposed by Akerlof (1997). I propose four different grouping criteria which account for geographical, demographic and economic issues; however, the results are not affected by the selected grouping criterion. The amplitude of peer group membership is here the key element to achieve identification without calling for the theoretical arguments (Brock and Durlauf, 2001) or more complex estimating procedures (Krauth, 2005). In fact, I assume that investment choice of each household has no impact on the mean peer choice, but, conversely, mean peer choice affects that of each individual. Because of this identifying assumption, standard estimation techniques may be applied. Probit results can be verbally sketched out in two main points. Firstly, social interactions matter and have a relevant impact on participation choice of Italian households and, secondly, strong incentive to imitate peers can lead to low level trap especially in geographical areas where stock market participation is quite infrequent or, at least, may explain the existence of stable subgroups avoiding entering stock market. Moreover, by making use of Vuong (1989) and Clarke (2003) tests to compare two rival non-nested models, I find that dynamic learning statistically dominates conformist model and this clear-cutting result entails some policy considerations. In particular, the stock market participation rate should not be too volatile following market performance and the effects of public interventions aiming at spreading *equity culture* can be greater due to the work of dynamic learning. Finally, I investigate the determinants of the adoption of dynamic learning versus conformist model whose proxy is derived by an auxiliary variable within the Clarke test. To this regard, I find that dynamic learning behaviour is supported by several sociodemographic variables mainly related to knowledge and human capital, whereas economic variables seem to be less relevant. However, as the dynamism in managing household portfolios increases, dynamic learning behaviour is significantly much more probable.

Concluding, even if the role of social interactions is greatly acknowledged, human capital seems to be the essence in the choice of entering financial markets, since it is the starting point for both entering stock market and, through social interactions, igniting virtuous learning mechanism.

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9 Figures and Tables

Figure 1: Participation, Peer Expectations and Risk Tolerance

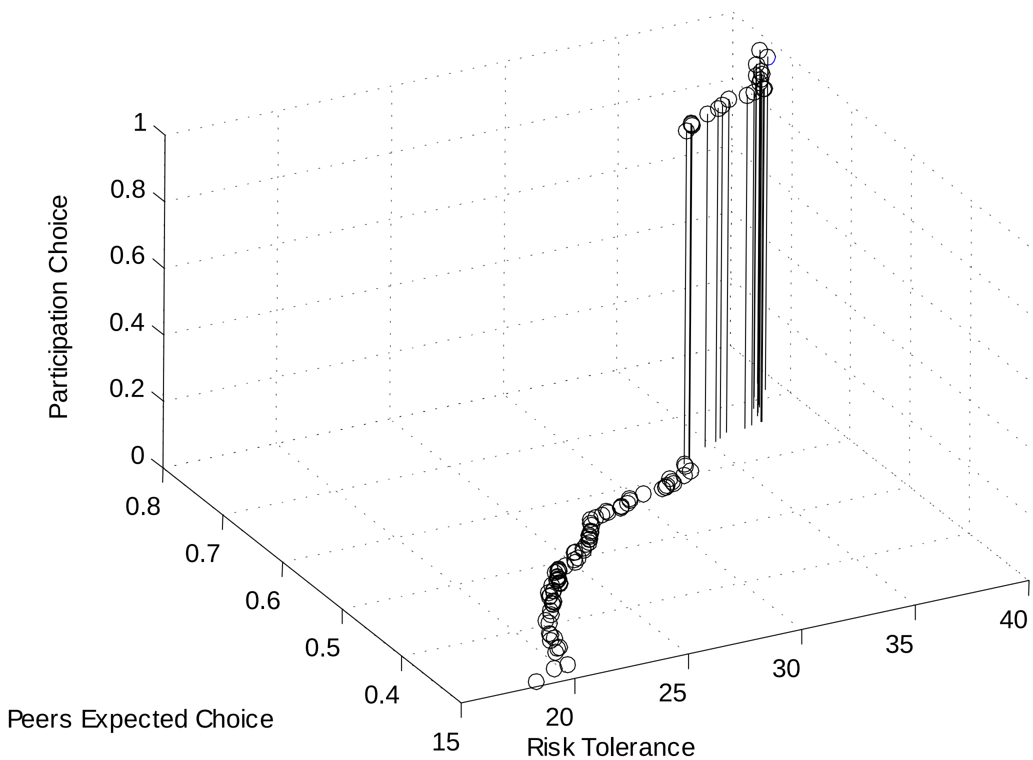

Figure 2: ...and the Impact of the Number of Contacts

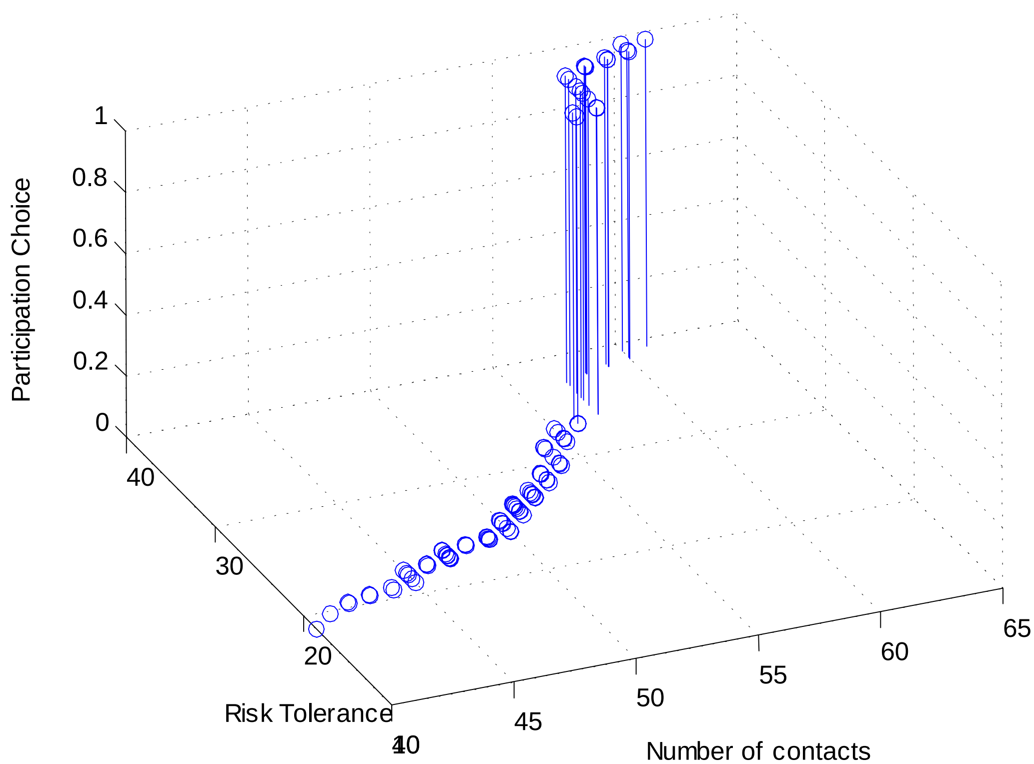

Figure 3: Social vs. Private Utility in Affecting Participation

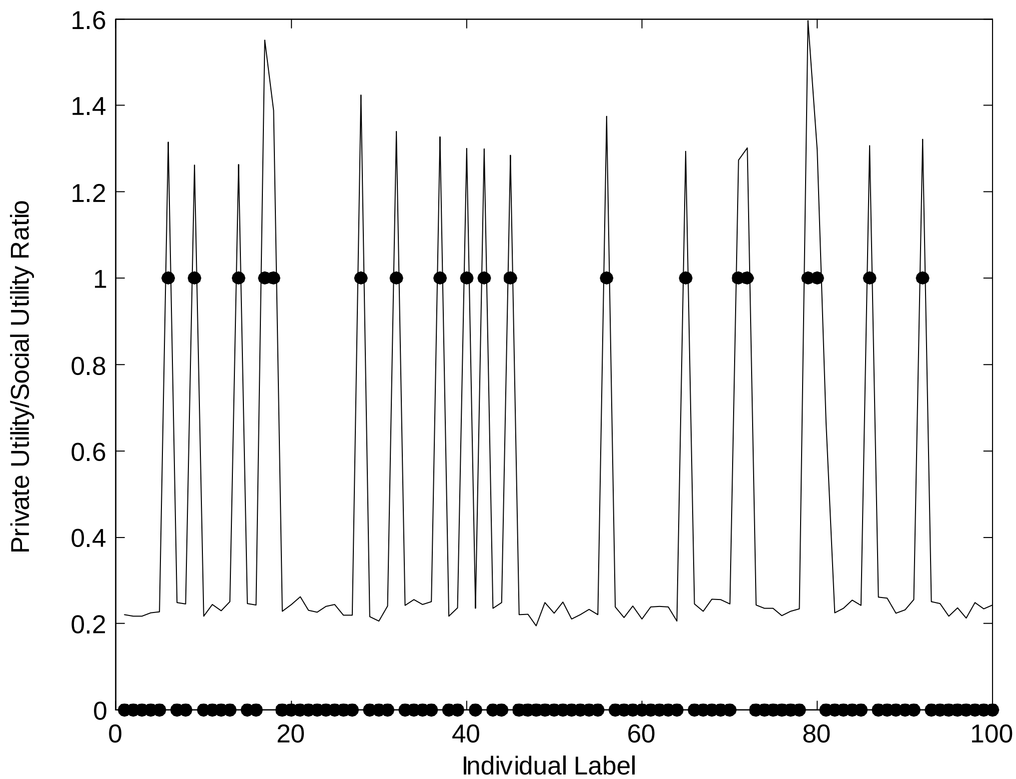

Table 1: Social Interactions and Participation Choice

Theory	Grouping Criterion	Correlation with Participation Choice
Conformist	Regional	0.1676*
	Regional & Dwelling Town Dims.	0.1905*
	Regional & Age Class	0.2151*
	Regional & Income Class	0.3173*
Dynamic Learning	Regional	0.1638*
	Regional & Dwelling Town Dims.	0.1809*
	Regional & Age Class	0.2024*
	Regional & Income Class	0.3106*

FOOTNOTES:

* denotes 1% statistically significant correlations.

Table 2: Social Indicators by Italian Regions (Source: ISTAT)

Region	TV	Post Off.	Bank	Newspaper	Books	Computer	Internet	Voluntary	Assoc.	Church	Sports
Piedmont	93.7	71.8	72.6	65.9	48.6	39.8	31.2	9.3	17.1	29.6	30.4
Valle d' Aosta	92.9	72.9	72.6	70	49.6	41.8	32.8	12.3	20	22.5	28
Lombardy	94.5	73.6	74.1	64.9	49.3	44.6	35.5	12.3	23	38.7	30.7
Trentino A.A.	92.8	71.9	83	75.6	50.3	45.4	36.3	21	28.8	38.4	33.2
Veneto	95.1	78.1	69.4	63.5	50.3	42.7	33.5	13	21.8	40.2	34
Friuli V.G.	93.5	77.4	70.9	73.2	51.8	40.5	31.4	10.6	18.6	24.4	37.2
Liguria	94.6	68.9	72.1	67.1	49.5	40.4	31.5	8	18.2	24.7	31.5
Emilia Rom.	96.8	75	75.9	67.8	46.5	42.8	35.2	10.6	25.3	24.4	30.9
Tuscany	95.8	70.7	68.5	62.5	47.5	41.5	31.8	10.6	22.6	20.3	30.4
Umbria	92.7	74.9	64.2	53.5	37.6	36.1	28.8	8.9	14.3	30.1	29.6
Marches	95.2	75.1	67.8	55.3	39.9	42.5	33.1	8.1	18	39.2	27.5
Latium	92.5	70	56.7	60.2	43.7	40.8	32.4	5	8.9	29.7	22.1
Abruzzo	95.5	77.7	59.9	53.7	38.6	39.3	30.3	5.9	13.9	41	26.7
Molise	96.3	78.8	49.2	44	31.3	38	27.4	6	12.6	38.6	26.6
Campania	94.8	67.2	41.2	43.1	28.7	33	25.9	4.6	9.7	44.6	20.9
Apulia	95.8	68.3	51.5	44.2	27.6	33.7	24.8	6.2	11.3	45.3	24.8
Basilicata	97.0	76.5	51.7	39.3	34	37.2	28.9	6.5	13.3	38.2	28.3
Calabria	95.2	71.9	42.6	42.2	28.5	33.7	23.2	4.1	8	36.4	21.1
Sicily	94.9	63.8	48.4	43.5	28.8	31.3	21.4	3.8	7.9	40.9	19.9
Sardinia	94.6	76.4	57.2	63.6	43.4	39.4	27.5	7.2	16.1	28.3	30.1
Italy	**94.7**	**71.8**	**62.5**	**57.6**	**41.4**	**39.2**	**30.3**	**8.5**	**16.5**	**35.2**	**27.4**

Table 3: Probit Estimates for Conformist and Dynamic Learning Model

Variables	Conformist Model	Dynamic Learning Model
number of household members	.0558391*	.0580916*
	(.0218412)	(.0217763)
sex	−.3587887*	−.3519972*
	(.0568553)	(.0566205)
schooling	.2447749*	.2472699*
	(.0151792)	(.0151562)
age	.0331333*	.0342506*
	(.0133012)	(.0133951)
age^2	−.0002316	−.00025**
	(.0001198)	(.0001209)
savings	$3.65E-06$*	$3.62E-06$*
	$(8.17E-07)$	$(8.19E-07)$
employment	.0328113**	.0302176**
	(.014939)	(.0148459)
banks	.0199865*	.0194623*
	(.0058356)	(.0059409)
cultural associations	−.0121136	−.0048816
	(.0094808)	(.0094532)
social interactions	5.014726*	2.969159*
	(.6050864)	(.4123035)
constant	−4.947138*	−5.029043*
	(.4680004)	(.4732711)
Number of obs.	8012	8012
Pseudo R^2	0.1913	0.1869
Correctly Classified Outcome (%)	93.10	93.14
LR test overall significance	770.60 (0.000)	753.03 (0.000)
Log-likelihood	−1629.1186	−1637.9001

NOTES:

* denotes 1%-statitically-significant coefficients.

** denotes 5%-statistically-significant coefficients.

Standard errors in parentheses.

Table 4: Testing the Exclusion of Social Utility Component

Model	LR Test
Conformist	$\chi^2\,(1) = 69.23$ (0.000)
Dynamic Learning	$\chi^2\,(1) = 52.06$ (0.000)

NOTES: P-values in parentheses.

Table 5: Conformism vs. Dynamic Learning

Test	Grouping Criteria			
	Region	Region & Town Dim.	Region & Age	Region & Income
Vuong (1989)	0.5083 (0.6113)	1.5363 (0.1245)	2.2273 (0.0259)	1.4178 (0.1562)
Clarke (2003)	4156 (0.0004)	4214 (0.0000)	4374 (0.0000)	4700 (0.0000)

NOTES: P-values in parentheses.

Table 6: The Determinants of Dynamic Learning Behaviour

Variables	Coefficients
number of household members	.0439967 (.0252413)
schooling	.0094396 (.0178442)
age	$-.0373346^{*}$ (.012175)
age^2	$.0004051^{*}$ (.0001064)
dwelling macroarea	$-.6679201^{*}$ (.0727207)
savings	$-8.21E-08$ ($8.62E-07$)
employment	$-.0284412^{*}$ (.0152239)
labour income quartiles	$-.0264831$ (.03217)
dimension of dwelling town	.0045412 (.0256318)
banks	$-.0678633^{*}$ (.008929)
cultural associations	$.0207039^{**}$ (.0098106)
time spent in monitoring investments	$-.0025469$ (.0303971)
dynamism of personal asset management	$.0368466^{*}$ (.0157748)
financial risk tolerance	.014928 (.0368885)
constant	5.726407^{*} (.7093938)
Number of obs.	2808
Pseudo R^2	0.0374
Correctly Classified Outcome (%)	59.22
LR test overall significance	145.50 (0.000)
Log-likelihood	-1873.2302

NOTES:

* denotes 1% statistically significant coefficients.

** denotes 5% statistically significant coefficients.

Standard errors in parentheses.