Quaderni FinTech

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Evidence from an experimental study

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La fiducia nel *robo advice*

Evidenze da uno studio sperimentale

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Sintesi del lavoro

Negli ultimi anni, la consulenza automatizzata (*robo advice*) ha conosciuto un notevole sviluppo, soprattutto nel contesto anglosassone. In parallelo, regolatori e autorità di vigilanza si sono interrogati e hanno adottato misure tese a mitigare i rischi per la tutela degli investitori, identificati sulla base di ipotesi circa le attitudini e le distorsioni comportamentali che potrebbero emergere tra i fruitori di *robo advice*. Il presente studio indaga sui comportamenti che potrebbero prevalere tra gli investitori più giovani, la categoria potenzialmente più interessata dal fenomeno, verificando se la propensione di un individuo a seguire una raccomandazione di investimento cambia a seconda che il consiglio venga formulato da un consulente umano ovvero da un *robo advisor*. A tal fine, il lavoro utilizza dati ed evidenze raccolti nell'ambito di un esperimento di laboratorio; tale esperimento ha coinvolto circa 180 studenti universitari della LUISS, sottoposti casualmente a due diversi trattamenti, e si è articolato in quattro fasi. Nella prima, i partecipanti hanno deciso come investire una (ipotetica) dotazione monetaria iniziale, fornita loro al momento dell'avvio dell'esperimento, scegliendo tra sei diversi portafogli di attività finanziarie caratterizzati da un diverso profilo rischio-rendimento. In seguito, dopo essere stati profilati attraverso un questionario standard utilizzato nella ricerca accademica (Grable and Lytton's Risk Tolerance Quiz), gli studenti hanno ricevuto (nella fase 2) una raccomandazione di

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investimento, coerente con il profilo di rischio individuato sulla base delle risposte al questionario, da un consulente umano ovvero da una piattaforma digitale appositamente sviluppata per l'esperimento (il *robo advisor*), a seconda del trattamento a cui erano stati casualmente assegnati. Nella terza fase, agli studenti è stato chiesto di scegliere di nuovo uno dei sei portafogli proposti. Nella quarta e ultima fase, i partecipanti hanno risposto a diversi questionari volti a rilevare una serie di variabili successivamente utilizzate nei modelli econometrici con i quali sono state stimate le determinanti della probabilità di seguire le indicazioni di investimento ricevute durante l'esperimento. I risultati ottenuti sembrano suggerire che la probabilità che un individuo segua una raccomandazione di investimento non dipende dalla natura del consulente (ossia prescinde dal fatto che il consulente sia fisico o digitale), bensì dal divario tra la scelta effettuata in autonomia prima di ricevere il consiglio e la scelta raccomandata dal consulente. Nel dettaglio, la probabilità che l'investitore sia disposto a seguire le indicazioni del consulente (umano o *robo*) aumenta se il portafoglio consigliato coincide con quello precedentemente scelto in autonomia. Tale evidenza potrebbe essere spiegata, tra le altre cose, da una propensione al cosiddetto '*confirmation bias'* (ossia l'attitudine a considerare tra le informazioni disponibili soprattutto quelle che confermano ipotesi e opinioni preesistenti). Nei casi in cui la scelta autonoma differisce dalla raccomandazione ricevuta, i partecipanti sembrano più propensi a seguire i consigli del consulente umano e meno propensi a seguire i consigli formulati da un algoritmo. Infine, i risultati mostrano che le studentesse partecipanti all'esperimento tendono a seguire i consigli ricevuti dal consulente fisico più di frequente se il consulente è una donna rispetto al caso in cui la raccomandazione sia stata formulata da un uomo.

Il presente lavoro è parte di un'indagine sul fenomeno del FinTech che CONSOB ha avviato nel 2016, in collaborazione con numerose Università italiane, con l'obiettivo di esplorare opportunità e rischi derivanti dall'applicazione dell'innovazione tecnologica all'offerta dei servizi finanziari. In particolare, lo studio integra il filone di ricerca dedicato al *robo advice* (Lener, Linciano e Soccorso, 2019, a cura di; Caratelli et al., 2019) con un contributo originale sui comportamenti di una specifica fascia di potenziali clienti di *robo advisor*, ossia i cosiddetti *millennials* e *post-millennials* che, secondo un approccio *evidence based*, potrebbero essere tenuti in considerazione nell'ambito di specifiche iniziative a tutela dell'investitore. Futuri sviluppi del lavoro potrebbero riguardare la percezione che le persone hanno della correttezza, dell'imparzialità e della trasparenza degli algoritmi utilizzati nell'offerta di servizi finanziari, ulteriori distorsioni cognitive che possono condizionare le scelte di investimento in ambiente digitale e le tecniche utilizzabili per mitigarne gli eventuali effetti pregiudizievoli per la tutela degli investitori.

Do investors rely on robots?

Evidence from an experimental study

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Abstract

Robo advice has moved its first steps in the Anglo-Saxon countries and is now rapidly gaining market share at a global level. The phenomenon fuelled a growing and still not conclusive institutional debate about potential benefits and risks to financial consumers, based also on investors' biases and behaviours that online platforms could trigger to the detriment of robo advisees. The present paper provides some insights into attitudes and behaviours that might prevail in a digital environment among young investors, representing the category of users potentially more involved by the development of the automated advice. In detail, the study investigates whether individuals' propensity to follow the recommendation received from an advisor changes depending on whether the advisor is a human or a robot. The analysis is based on data collected through an *ad hoc* developed laboratory experiment run in the Cesare Lab of LUISS University with a sample of 180 students. Students were given an initial monetary endowment and were asked to choose between six different portfolios of financial activities; after being profiled through a questionnaire aimed at eliciting their risk tolerance (Grable and Lytton's Risk Tolerance Quiz; 2003), they received the advice, either from a human advisor or from a robo advisor (i.e. via a computer platform) depending on the treatment they had randomly assigned before entering the experimental session. Then, they were asked again to choose among the six portfolios in order to capture whether the propensity to follow the recommendation depends on its source

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(human versus robo). Finally, participants were asked to answer several questions eliciting risk preferences, financial literacy (actual and perceived) and digital literacy, serving as control variables when modelling the probability to follow the advice.

Our results show that the probability to follow the advice does not depend on the source of the recommendation but rather on the alignment between the self-directed choice made before receiving the advice and the recommendation subsequently received: the propensity to follow the advisor (either human or robo) increases if the advice confirms individual's own beliefs about her/his investor profile. This result might be explained by referring to individuals' attitude towards the so called 'confirmation bias'. However, when the self-directed choice differs from the recommendation received, participants may be more likely to follow the advice given by a human advisor and less likely to follow the advice formulated by an algorithm. Also the gender of the advisor seems to matter: women tend to follow the advice provided by a female advisor more frequently compared to the case of the recommendation given by a male advisor.

This work is part of a wider research on FinTech that CONSOB started in 2016, in collaboration with several Italian universities, with the aim of exploring opportunities and risks for investor protection and the financial system as a whole, related to the application of technological innovation to the provision of financial services. In particular, supplementing Lener, Linciano and Soccorso (2019, edited by) and Caratelli et al. (2019), this document widens the field of investigation by referring to a specific target of the population - the so called *millennials* and *post-millennials* – and using complementary and innovative methods.

According to an evidence-based approach, insights from the present study may suggest specific investor protection initiatives, also in terms of financial education activities designed for a clearly-identified segment of the population (the so called *millennials* and *post-millennials*, in this case).

Evidence from the present work might be extended further with respect to the consumers' perception of the fairness of algorithms used to provide financial services, the cognitive heuristics and biases underlying decision making process and investments in the digital environment and nudges which may be used to enhance investor protection.

JEL Classifications: C91, D12, G11, G41.

Keywords: FinTech, digitalisation, *robo advice*, MiFID II, portfolio choice, investment decisions, experimental analysis, laboratory.

Contents

1 Introduction and main conclusions

Technological innovations are rapidly changing the provision of financial services to retail investors. In particular, robo advice, based on customised investment recommendations about financial instruments processed by algorithms and delivered via digital platforms, moved its first steps in the Anglo-Saxon countries and is now rapidly increasing its market share at a global level. The ongoing development of digitalisation, in general, and automated advice, in detail, has already fuelled a growing and still not conclusive institutional debate about potential benefits and risk to investors and market participants (European Commission, 2016; ESAs JC, 2016; IOSCO, 2017).

With regard to robo advice, in particular, doubts are raised about investors' capability of understanding the service characteristics, reading and understanding financial information in the digital environment, filling in autonomously a questionnaire aimed at profiling their characteristics (the so called suitability questionnaire) and making sound decisions after taking advice from a robot. On this points, ESMA (2018) has released guidelines suggesting some measures that could mitigate the risk of detrimental effects to the users of robo advice.[1]

At the same time, the academic literature has started to delve deeper into attitudes and behaviours that could prevail among robo advisees, sometimes casting from the investigation on online shopping.

The present paper provides some insights into attitudes and behaviours that might prevail in a digital environment among young investors, representing the category of users potentially more involved by the development of the automated advice. In detail, the study investigates whether the participants to an experiment exhibit different propensity to follow the recommendation received from an advisor depending on whether the advisor is a human or a robot.

To this aim, a laboratory experiment was designed and run in the Cesare Lab of LUISS University in Rome. The experiment engaged about 180 students attending Economics, Law and Political Science courses of LUISS University and encompassed four stages. First, students were given an initial monetary endowment and were asked to choose between six different portfolios of financial activities; after being

1 To address potential gaps in clients' understanding of the robo advisors' services ESMA asks firms to explain that the answers investors provide will have a direct impact in terms of the suitability of the recommendation and to give investors a description of the sources of information used to generate the advice («*e.g., if an online questionnaire is used, firms should explain that the responses to the questionnaire may be the sole basis for the robo-advice or whether the firm has access to other client information or accounts*»; Supporting guideline no. 20). Acknowledging the crucial role of information in investors' choices, ESMA states that robo advisors should emphasise all «*the relevant information (e.g., through the use of design features such as pop-up boxes)*» and consider whether «*some information should be accompanied by interactive text (e.g., through the use of design features such as tooltips) or other means to provide additional details to clients who are seeking further information (e.g., through F.A.Q. section)*» (Supporting guideline no. 21). In addition, robo advisors should take into account «*whether the questions in the questionnaire are sufficiently clear and/or whether the questionnaire is designed to provide additional clarification or examples to clients when necessary (e.g., through the use of design features, such as tool-tips or pop-up boxes)*» and «*whether some human interaction (including remote interaction via emails or mobile phones) is available to clients when responding to the online questionnaire*» (Supporting guideline no. 32).

profiled through a questionnaire aimed at eliciting their risk tolerance. Second, they received the advice, i.e. they were told which of the six portfolios best suited their investor profile, either from a human advisor or from a robo advisor (i.e. via a computer platform) depending on the treatment they had randomly assigned before entering the experimental session. Third, they were asked again to choose among the six portfolio in order to capture whether the propensity to follow the recommendation depends in its source (human versus robo). Fourth, participants were asked to answer several questions eliciting risk preferences, financial literacy (actual and perceived) and digital literacy, serving as control variables when modelling the probability to follow the advice.

Our results show that the probability to follow the advice does not depend on the source of the recommendation (human versus robo advisor) but rather on the alignment between the self-directed choice made before receiving the advice and the recommendation subsequently received. In particular, the propensity to follow the advisor (either human or robo) increases if the advice confirms individual's own beliefs about her/his investor profile. This might be explained by referring, among others, to individuals' attitude towards the so called 'confirmation bias'. On the other hand, when the self-directed choice differs from the recommendation received, participants may be more likely to follow the advice given by a human advisor and less likely to follow the advice formulated by an algorithm.

The probability to follow the advice is not affected by none of the considered control variables describing some individual characteristics of the participants (i.e. field of study - Economics *versus* other subjects -, risk aversion, actual and perceived financial knowledge and digital literacy), whilst the gender of both the advisor and the advisee seems to matter. Women tend to follow the advice provided by a female advisor more frequently compared to the case of the recommendation given by a male advisor. This result is robust to all the main model specifications. There is also weaker evidence on male participants being less willing than female to follow a female professional.

This work is part of a wider research on FinTech that CONSOB started in 2016, in collaboration with several Italian universities, with the aim of exploring opportunities and risks for investor protection and the financial system as a whole, related to the application of technological innovation to the provision of financial services. In particular, supplementing Lener, Linciano and Soccorso (2019, edited by) and Caratelli et al. (2019), this document widens the field of investigation by referring to a specific target of the population - the so called *millennials* and *post-millennials* – and using complementary and innovative methods (i.e. lab experiments).

The methods of investigation based on experimental economics used in the present study allowed authors to test the factors affecting the propensity to follow the advice of the targeted subjects (in this case, *millennials* and *post-millennials*), deciding under controlled conditions. As the methodology suggests, we controlled in terms of both the homogeneity of the characteristics of the subjects participating in the experimental session and the options of choice and the modes of interaction envisaged. In detail, participants were all students, exhibiting low variability in critical characteristics such as age, education level, financial and digital literacy. Moreover, the experiment has been designed in order to prevent the comparison between the two treatments from being biased by factors others than the perceived trustworthiness of the algorithm: human advisors were not allowed to provide clarifications either on the suitability questionnaire or on the investment options, thus the 'human touch effect' of the advisors engaged in the experimental session was unable to affect results.

The present work adds to the existing literature broadly referred to the human-computer interaction and the behaviour of online customers by specifically focusing on digitalised financial services and on the propensity to follow the advice received from a robot.

According to an evidence-based approach, insights from the present study may suggest specific investor protection initiatives, also in terms of financial education activities designed for a clearly-identified segment of the population (the so called *millennials* and *post-millennials*, in this case).

Evidence from the present work might be extended further with respect to the consumers' perception of the fairness and transparency of the algorithms used to provide financial services, the cognitive heuristics and biases underlying decision making process and investments in the digital environment and nudges which may be used to enhance investor protection.

2 Trust as a driver of the demand for financial advice: a review of the empirical literature

2.1 The case of human financial advice

Trust in financial system and in financial intermediaries plays a crucial role in many stages of an individual's investment decision making. It prompts stock market participation as well as the demand for human financial advice (CONSOB, 2015-2019; Linciano et al., 2016; Guiso, et al., 2008; Madamba, 2020). Trust is also a heuristic allowing investors to make choices that are based on subjective expectations and on 'proxies for trustworthiness' rather than on true and detailed information (Altman, 2014; Cruciani et al., 2018) as it can be described as the confidence based on «*personal relationships, familiarity, persuasive advertising, connections to friends and colleagues, communication, and schmoozing*» leading investors to rely on the advisors which may appease their anxiety and help them to invest (Gennaioli et al., 2015).[2]

Interestingly, trust is positively correlated with financial literacy, which in turn some studies found to be positively associated to financial advice seeking (Bachmann and Hens, 2014; Bluethgen et al., 2008; Bucher-Koenen and Koenen,

2 Bergstresser et al. (2009) assert that some investors prefer to rely on their advisors despite inferior portfolio outcomes since they receive other, less tangible, benefits from their advisor relationship (e.g. advisors increase overall investor comfort with their investment decisions).

2015; Calcagno and Monticone, 2013; Collins, 2012; Debbich, 2015; Hackethal et al., 2012; Van Rooij et al., 2007), while a negative mismatch between perceived and actual capability (proxing the so called overconfidence) discourages advice seeking (Linciano et al., 2016).

Some authors find that women have a higher propensity to delegate (Bluethgen et al., 2008; Calcagno and Monticone, 2013; Guiso and Jappelli, 2006; Hackethal et al., 2012; Kelly, 1995; Linciano et al., 2016), whereas others highlight the opposite result (Bhattacharya et al., 2012) or no gender difference at all (Hackethal et al., 2012).

In addition, many other factors may impact on financial advice seeking and advisor-client relation. Beyond the well-known framing effect, that is the way financial information is disclosed, whose impact on risk perception and risk taking has been investigated by an extensive strand of the experimental and behavioural literature,[3] many behavioural biases due to emotion or cognitive limits[4] may be relevant on both the advisor side and the investor side.[5] In detail empirical evidence was gathered on investors' attitude to emphasise information and recommendations that confirms their beliefs while ignoring contradictory data (Cheng, 2019; Golman et al., 2017; Rigoni, 2016), while Cerulli Associates and Charles Schwab Investment Management (2019) find confirmation bias to be among the most significant behavioural biases affecting clients' investment decisions.

Both advisor and investor cognitive distortions are likely to influence portfolio choices (Glaser et al., 2005; Linnainmaa et al., 2018), as advisors themselves may not be aware of their own biases and/or may not be willing to debias their customer financial decision making.[6]

3 As for the Italian case, Linciano et al. (2018), investigating the impact of financial disclosure on risk perception, risk tolerance and propensity to invest. Additional factors affecting risk perception, risk tolerance and risk taking have been identified, including socio-demographic characteristics, personal traits such as gender, age and financial literacy (actual and perceived; as for a review of these individual traits see, among the others, Linciano and Soccorso, 2012; as for gender effect on risk tolerance, see Baeckström et al., 2018a and 2018b; Charness and Gneezy, 2012; Eckel and Grosmann, 2002; Merrill Lynch, 1996).

4 Advisor cognitive distortions may also be grounded into conflict of interests. Cain et al. (2005) in their experiment find that people generally do not take into account biases caused by conflicts of interest of advisors as much as they should, feeling that the disclosure about conflict of interests shows advisor's trustworthiness. Experimental data by IFF Research and YouGov (2009) show, instead, that the disclosure of conflict of interests can go unnoticed, unless it is done in a very salient way which ends up generating total distrust and a priori refusal to follow the advice even when it would be appropriate to do so (so-called knee-jerk effect). For further discussion, see also Fisch and Turner (2017).

5 Several authors paid a great deal of attention to the biases affecting investors' behaviours (Baker and Ricciardi, 2014; Kahneman, 2011; Linciano, N., 2010; Patt and Zeckhauser, 2000), and to behavioural mistakes recurrent during financial crisis and market downturns (Economou et al., 2017). In particular, empirical studies show that households hold under-diversified and home-biased portfolios (Blume and Friend, 1975; Calvet et al., 2007; Goetzmann and Kumar, 2008; Huberman, 2001; Kelly, 1995); are prone to availability and familiarity heuristics (Barber and Odean, 2008), trade too much (Odean, 1999), sell winners too early while holding losers too long (Shefrin and Statman, 1985; Odean, 1998).

6 From a theoretical point of view, professionals may have a strong incentive to pander investors beliefs, since pandering induce investors trusting their professional to invest more and at higher fees (Gennaioli et al., 2015). As for empirical (survey) evidence, Cerulli Associates and Charles Schwab Investment Management (2019) survey on how advisors handle misalignments between their clients' preferences and capacity to take risk found that more 27% of the advisors typically adjust to or accommodate their clients' risk preferences, while only 16% seek to

2.2 The case of robo financial advice

In the face of the growing digitalisation of the financial services, it is key to understand the drivers of the so-called e-trust that grows «*as we are learning and as we are developing skills for dealing with these new entities*» (Coeckelbergh, 2012).[7]

As already occurring in the e-shopping, the search for innovative, effective and personalised methods is already orientating towards digitalised financial products and services (e.g., the online banking). This trend may be further accelerate by the Covid-19 pandemic also with respect to robo advice and even in Italy where it still concerns a limited group of users (Lener, Linciano and Soccorso, 2019, edited by).

Robo advice may be attractive to investors because of minimum investment thresholds and fees lower than those envisaged by a 'human' advisor, as well as because of the usability and accessibility of digital platforms.[8] On the other hand, low technology acceptance and low propensity to use digital tools for personal finance management may act as a deterrent.[9]

Caratelli et al. (2019) delve further into this by gathering and discussing qualitative evidence on the drivers of trust in financial advice both in the digital and in the human environment. A robo advisor may be perceived as more reliable than a human advisor due to the perceived objectivity of the algorithm and the standardisation of the model portfolios,[10] both granting that individuals with the same financial profile are recommended the same investment, whereas a human professional may behave on 'a discretionary basis' and deliver an unsuitable recommendation either because not acting in the best interests of the customer or by mistake and lack of competence. Nevertheless, on the emotional side, the appreciation of the perceived objectivity of the automation underpinning robo advice is balanced by the negative feelings driven by the lack of a stable and empathic human relationship, the perception of being forced to decide autonomously, and the anxiety grounded in one's own low financial and digital competence.

A key research question is whether and to what extent the digital environment leads advisees to act differently from what they would do in the interaction with a physical advisor. The literature on online consumers' behaviour has

increase clients' comfort level with risk. Empirical evidence about a sample of Italian advisors shows instead that most advisors assert to not take into account emotions and cognitive limits of their clients and elaborate their recommendations by relying only on technical analysis (CONSOB, 2018).

7 With respect to online shopping, some studies investigated the mindset of online shoppers and uncovered many of the triggers of online choices, finding that online behaviours are activated by different kind of 'impulse' with respect to traditional purchasing channels. These studies, both theoretical and empirical, explore the role of peer recommendations and reviews in e-shopping (PtoPIQ, 2016), the impact of the variability of visual elements available in the digital environment as well as the role of behavioural biases in accessing, filtering and analysing information available online (Benartzi and Lehrer, 2017; Directorate General for Internal Policies, 2011).

8 According to some empirical evidence, the cost of service may play a minor role, since most investors do not have a clear understanding of the price they pay for advice and are not able to ascertain the 'value-for-money' of the service (CONSOB, 2015-2019 and Madamba, 2020).

9 As for the role of personal values as sources of motivation with respect to online shopping, among others please see Katawetawaraks and Wang (2011) and Koo et al. (2008).

10 However, research on the perception of fairness of algorithms in financial services is not conclusive (Behavioural Insight Team, 2019).

brought evidence on some interesting features that may be inspiring for research in the area of digital financial services.

A number of authors have investigated the differences between web surveys and other data collection methods, either in terms of response rate and data quality or in terms of propensity to use response-scale or to answer 'don't know' (e.g., Duffy et al., 2005; Heerwegh and Loosveldt, 2008).[11] Such differences might be driven by many factors. Duffy et al. (2005) highlighted the so called 'interviewer effect' and 'social desirability bias' that, while potentially relevant in face-to-face methodologies, do not play any role in online surveys. Indeed, these latter, as they do not envisage the interaction with interviewers, may prompt more reliable answers about 'undesirable' behaviours and self-assessed knowledge and abilities. This evidence might be relevant also in the field of investigation relating to financial advice as investors have to fill in the so called suitability questionnaire in order to be profiled by the advisor and as the reliability of the information provided by the investors may vary depending on whether the advisor is a human (prone to support and/or to administer the questionnaire) or a robo (requiring the customer to autonomously fill in the format available online). To this respect, however, ESMA (2018) highlights that the risk of overestimation of one's own knowledge and experience is higher when investors «*provide information through an automated (or semi-automated) system, especially in situations where very limited or no human interaction at all between clients and the firm's employees is foreseen*».[12] This topic deserves further investigation.

In addition, some authors suggest that online investment choices may be sensitive to a number of factors peculiar of the digital environment affecting both the perception and use of financial information and the propensity to follow the recommendation received from the advisor.

As for the former issue, framing effects may be strengthened by the online environment of a pure robo advisor (i.e. a platform excluding any interaction other than a that with a chatbot) compared to the interaction with a physical advisor, since the processing of information is fully left to the autonomous judgment of the client. However, thanks to the use of technology, this effect may be mitigated through visual, flexible and interactive online tools as well as properly designed automated procedures and graphic interfaces stimulating behaviour in the investor best interest, in line with the most advanced nudging techniques (Box 1). On the other hand, online providers could use technology to misguide consumer perceptions to their advantage. On this point further investigation is needed.

11 Among the strand of literature that may be relevant to the present work, it is worth mentioning the empirical studies that explored the difference between data collected through a questionnaire filled in online with respect to a questionnaire administered vis-à-vis (Duffy et al., 2005; Heerwegh and Loosveldt, 2008) and enumerate a number of factors that might be relevant also when comparing results obtained through suitability questionnaires filled in online autonomously by investors or administered by human advisors. Although interesting, findings about attitudes of online shoppers cannot lend itself to be generalised to online financial services since they may vary across product categories.

12 ESMA (2018) recommended robo advisors, in particular, to adopt mechanisms to address this risk (see Supporting guideline no. 51).

Box 1

The digital nudge

According to Thaler and Sunstein (2008), a 'nudge' is «*any aspect of the choice architecture that alters people's behavior in a predictable way without forbidding any options or significantly changing their economic incentives*».

Nudging may consist in minor intervention within the choice architecture aimed at prompting individuals to make something which leverage specific psychological effects, preserving people freedom of choice. For instance, nudging is at the base of Thaler's Save More Tomorrow tool, aimed at overcome people present-bias and their troubles with saving for retirement (Thaler, 2017).

Extending this concept to the digital context, 'digital nudging' may be considered as the use of user-interface design elements (such as colours, images, wording) to guide people's behaviours in digital choice environments (Weinmann et al., 2016). Implementing nudges in the digital context can be done at a lower cost, compared to traditional environment, thanks to digital specific affordance which make them potentially more customisable and effective.

Mirsch et al. (2017), in their theoretical work, provide an overview of relevant psychological effects of nudging and provide examples of digital nudges.

Also robo advisors could *'interact graphically with clients, nudging them to make better informed financial decisions'* (Finametrica, 2015). Indeed, robo-advisors can make use of enhanced nudging techniques which are not feasible or effective in traditional face-to-face relationships (Benartzi, 2017).

As for the second issue, that is the propensity to follow the received recommendation, the nature of the advisor (human versus robo) may prompt different drivers of the reliance on advisors' suggestions. In the interaction with a human professional, beyond investors' socio-demographics, personal traits and previous experience with financial intermediaries and investments, advisees' inclination to invest as recommended may build on elective affinity, personal connection, perceived commonality of languages, expectations, goals, gut feelings, gender effect and so forth (CONSOB, 2015-2019; Baeckstrom et al., 2018a; Caratelli et al. 2019; Madamba et al., 2020). In the online environment, instead, the perceived objectivity of the algorithm generating the recommendation,[13] the user's digital literacy and his/her

13 In general, it can be said that human advisors have the potential to subtly but consequentially influence their clients' choices (Foerster et al., 2017a and 2017b), while robo advice is generally more transparent and objective than the advice of human advisors (Fisch and Turner, 2017). Loos et al. (2019) investigated the effect of robo advisors on investors' portfolio choices in order to verify if robo advice promotes financial risk-taking and mitigates biases and find that joining a robo advisor has a positive effect on portfolio diversification and portfolio efficiency, since clients increase financial risk-taking, prefer diversified portfolios and exhibit lower home bias. In their field experiment Loos et al. (2019) compared users of robo advisor, bank clients advised by a human advisor and self-directed clients and find that the above mentioned effects are generally stronger for former self-directed investors than investors who have previously worked with a human financial advisor. Nonetheless, few empirical evidence has been collected about how robo advice affects investment portfolios and whether it offers actual benefits compared to human advice.

online experience may come to play a crucial role. User experience is a multifaceted concept, indeed, as it «*is a consequence of a user's internal state (predispositions, expectations, needs, motivation, mood, etc.), the characteristics of the designed system (e.g. complexity, purpose, usability, functionality, etc.) and the context (or the environment) within which the interaction occurs (e.g. organisational/social setting, meaningfulness of the activity, voluntariness of use, etc.)*» (Hassenzahl and Tractinsky, 2006).

An additional point is the role of behavioural biases. As said above, confirmation and gender biases may be among the cognitive distortions leaning individual's reliance on the advisor. To this respect, while online interaction with a robo advisor may do away with some biases of both investors and human advisors,[14] as already mentioned it may bring other distortions that need to be address, related to the usability and functionality of online tools, framing effect and the individual level of technology acceptance.

To sum up, the evidence on investors' biases and behaviours that could be triggered by a robo advisor is ongoing and still not conclusive. The present paper provides some insights into attitudes and behaviours that might prevail in a digital environment among young investors, representing the category of users potentially more involved by the development of the automated advice. In detail, the study investigates whether individuals' propensity to follow the recommendation received from an advisor changes depending on whether the advisor is a human or a robot. The analysis is based on a laboratory experiment whose design and procedures are detailed in the following.

3 The experimental design and procedures

The experiment was run in the Cesare Lab, LUISS University in Rome, and involved 178 participants recruited from a pool of students in Economics, Law and Political Science through Orsee (Greiner, 2015). The experiment included 14 sessions. Subjects participated in one session only. The software used for the experiment was Z-Tree (Fischbacher, 2007).

At the beginning of each session the experimenter read aloud the written instructions before participants could privately ask for clarification and start the experiment (the translated version of the Instructions is reported in Appendix 1).

At the end of the experiment some questionnaires were handed to participants in order to collect demographics and other individual characteristics.

Each experimental session consisted of four stages and a final questionnaire, which all participants went through to complete the experiment:

14 It can be assumed that robo advisors are less likely to be affected by biases, such as gender biases. For instance, Mullainathan et al. (2012) indicate that financial advisors are systematically less likely to ask women their age than men, whilst robo advisors do not exhibit such a bias.

i. *Stage I*: Participants make an initial investment choice and are profiled on the basis of a questionnaire;

ii. *Stage II*: Participants are given financial advice;

iii. *Stage III*: Participants make their investment decision, that may be in line or not with the advice received a Stage II;

iv. *Stage IV*: Participants choose between lottery pairs with the aim to elicits their attitude toward risk.

v. *Questionnaires:* Participants answer additional questionnaires.

At *Stage I* participants were given an initial monetary endowment expressed in experimental tokens (the conversion rate between experimental tokens and actual monetary payoffs was included in the Instructions). Then, they were asked to invest the whole monetary endowment in one of six different portfolios of financial activities characterised by different risk-return profiles (i.e., different combinations of variance and expected value) according to their own preferences. Afterwards, participants were asked to fill the (translated version and with monetary values in euros) Grable and Lytton's Risk Tolerance Quiz (2003; see Appendix 2 for the original version). Their answers were used to profile their risk preferences and to identify the portfolio that best suited them among the six proposed.

At *Stage II*, participants received the advice either from a computer or from a human advisor, according to the treatment randomly assigned at the recruitment stage. If assigned to the *Treatment H(uman)*, participants individually moved to a room different than that of *Stage I* where they met a financial advisor. The advisor handed them a folder with the investment advice recommending the portfolio best suited to their profile (identified on the basis of the answers previously given to the Grable and Lytton's Risk Tolerance Quiz). If assigned to the *Treatment R(obo)*, participants individually moved to a room different than that of *Stage I* where they found a single folder with a print-out reporting the investment advice recommending the portfolio best suited to their profile. Individuals undergoing different treatment would receive the same portfolio recommendation if they had the same profile. Treatments differ with respect to what participants were told about the source of their advice. In the H Treatment they were told that a human advisor would look at their questionnaire answers and deliver them a recommendation: in detail, after having answered to the profiling questionnaire, they were asked to go into another room, where the human advisor gave them a folder with the printed recommendation, saying the following words: «*On the basis of your risk profile, stemming from your answers in the questionnaire, I elaborated the present recommendation…*». In the R treatment they were told that an algorithm would calculate their recommendation based on their answers: in detail, after having answered to the profiling questionnaire, they were required to inspect their advice on the computer screen where they read the following words: «*On the basis of your risk profile, stemming from your answers in the questionnaire, the computer elaborated the present recommendation…*»; finally, they were asked to go into another room where they found their recommendation printed in a folder (this last step was needed in order to ensure homogeneity in the Treatments).

At *Stage III,* after having received the advice, participants were asked if they wanted to revise their investment decision by reallocating their endowment to one of the six portfolios shown at *Stage I*, other than that previously chosen.

At *Stage IV* participants concluded the experiment by answering the following tasks aimed at eliciting risk attitudes (Holt and Laury, 2002; see Appendix 1).

A final questionnaire allowed to collect information about financial literacy (Lusardi and Mitchell, 2014; Van Rooij et al., 2011), self-assessment of own financial knowledge and digital literacy (Hargittai, 2009), alongside with the participants' socio-demographic characteristics (all questionnaires are reported in Appendix 2).

3.1 The portfolio investment task and the questionnaire

As mentioned above, during the same experimental session, participants took the same type of investment decision twice: first, they made a 'self-directed choice', by autonomously choosing one out of the six portfolios available (*Stage I*); second they made an 'advised choice' conditioned by the advice received (*Stage III*). The treatments differ by the source delivering the advice, either communicated through a computer (no advisor is involved) or by a human advisor.

Both choices involve the same portfolio options, generated through the Black-Litterman model (Box 2).

Box 2

The optimal portfolios recommended to participants

The portfolios shown to participants in the experiment were defined by using the Black-Litterman Model (1991,1992). This model was preferred to Markowitz (1952,1956), which allows to generate optimal portfolios weights by solving a constrained quadratic optimisation problem, in order to lessen certain limitations related to the traditional mean variance approach such as the high sensitivity of the weights to expected rates of returns and the problem of estimation error maximization.

The Black-Litterman model attempts to effectively incorporate investors' views into the portfolio optimization problem to obtain a more instinctive set of weights, which may better reflect the current market trends. In addition, it is an important and popular asset allocation model among asset managers and recently also among robo advisors.

On the basis of this sound theoretical background and in the light of the widespread industry practice, we generated six optimal portfolios by employing Black-Litterman. These portfolios represented six recommended asset allocations with distinctive risk-return profiles, but equivalent cognitive burden, as all of them include six asset classes, except the more conservative one counting only five asset classes.

The portfolios have different risk-return profiles (Table 1). Portfolio 1 is the safest investment, characterised by the lowest expected return as well as the lowest variance. Riskiness increases throughout portfolios, till Portfolio 6 having the highest variance as well as the highest expected return.

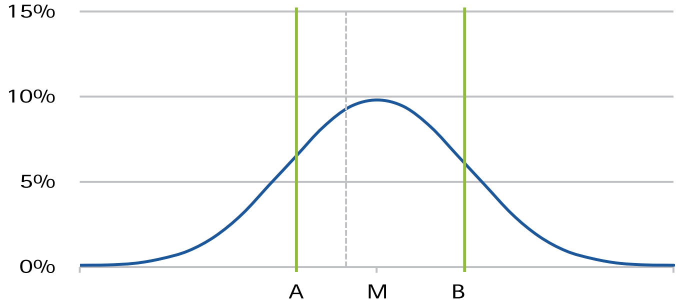
Table 1 – Risk-return characteristics of portfolios

	expected returns (ER)	sigma	std. dev. (%)	EV/std.dev.
portfolio 1	1.80%	2.46	2.46%	8.276
portfolio 2	2.61%	3.27	3.27%	6.276
portfolio 3	3.14%	4.13	4.13%	4.995
portfolio 4	3.54%	4.86	4.86%	4.261
portfolio 5	4.03%	5.80	5.80%	3.587
portfolio 6	4.38%	6.49	6.49%	3.217

The experimental design aims to mimic the risk-related decision making made by individuals participating in financial markets. However, in order to prevent ambiguities in the interpretation of the investment choices made by the participants in the experiment, no mention was made on the assets included in each portfolio. As a way of example, if portfolios had been described not only in terms of expected returns and variance but also with respect to the share of domestic and foreign stocks, it would have been impossible to disentangle the impact on the participants' choices due to the portfolio risk-return characteristics from the impact due to the asset allocation. Furthermore, in the experimental setting the expected return and variance of the portfolios are a stochastic result and no additional market information would have helped to make a better decision. In other words, the experimental design forced participants to strictly focus on perceived risk in itself. [15]

Each portfolio was represented as the distribution of the expected returns, with the dash line representing zero return (see Figure 1). The average return is represented by M, while A and B included the 68% of the distribution. Values M, A, and B were specified for each portfolio, in order to represent both the average return and the variance of the investment.

Figure 1 – Portfolio representation



15 It would be cognitively interesting to study the subjective belief dimension in the financial market, but this study does not consider this feature.

After taking the first investment choice in *Stage I*, as already said, participants answered the Grable and Lytton's Risk Tolerance Quiz (2003) and some additional questions actually used by Italian robo advisors that were used to test inconsistencies without entering the risk profile assessment. Based on the answers collected, for each participant the portfolio best suiting her/his risk preferences was identified among the six available portfolios.

3.2 Experimental design and treatments

Participants to the experiment were assigned to the Treatments as follows: 116 subjects to ***Treatment H*** (i.e., slightly more than 65% of the total) and 62 subjects to ***Treatment R*.**

With respect to possible biases resulting from significant differences in the characteristics of the participants assigned to the two Treatments, data shows a (weak) difference in the experimental experience, as participation in more than five experiments is recorded in 42% of the cases for the subjects assigned to *Treatment R* and in 29% of the cased for those in *Treatment H*. A weak difference between the two samples is detected also with respect to age, while no significant difference is recorded with respect to gender, financial literacy and digital literacy (Table 2).

Table 2 – Demographics characteristics of participants

SUMMARY STATISTICS

	obs.	mean	std. dev.	min	max
female	178	0.449	0.499	0	1
age	178	22.618	2.531	18	32
economics	178	0.618	0.487	0	1
financial literacy	178	2.904	1.061	0	5
self-assessed financial lit.	178	4.848	2.296	1	9
digital literacy	178	3.493	0.921	1	5
risk id	178	0.474	0.199	0	1

BALANCE TABLE

	mean (H)	mean (R)	difference	description
female	0.48	0.39	0.10	participant's gender
age	22.37	23.08	-0.71*	participant's age
experienced	0.29	0.42	-0.13*	participated in more than 5 experiments (dummy)
easy	0.88	0.94	-0.06	found the experiment was easy (dummy)
economics	0.65	0.56	0.08	student of economics (dummy)
financial literacy	3.05	2.93	0.12	financial literacy score
self-assessed financial lit.	4.91	4.73	0.19	perceived (i.e. self-reported) financial knowledge
digital literacy	41.19	41.79	-0.60	digital literacy score

Notes: N=178; *** means significant at 1%, ** significant at 5% and * significant at 10%.

Participants could not participate to both treatments, nor were they aware of the existence of the other treatment. Subjects undergoing Treatment H do not have the possibility to ask for clarification to the human advisor: this reduced variability in observed choices due to factors other than the source of the advice and the perceived reliability of the algorithm.

In order to capture any possible gender effects in the relation between the investor and her/his advisor (Baeckström et al., 2018a and 2018b), four different advisors are employed in *Treatment H*: two males and two women, of roughly the same age.

3.3 The elicitation of risk aversion

In *Stage IV*, the individual risk aversion was elicited through the traditional Holt and Laury (2002) protocol, including the series of ten pairwise lotteries listed in Table 3. Participants were presented a visual task, as they saw each couple of the ten lotteries separately as shown in Figure 2, with the left lottery always representing the safer one and the right lottery standing for the riskier one. In Figure 2, the left lottery (the safer) allows to win 3 euros with a 60% probability and 5 euros with a 40% probability, while the right lottery (the riskier) the payoff is 8.50 euros with 60% probability and 0.3 euros with 40% probability.

Table 3 – Pairwise lotteries, Holt and Laury's protocol

task	safe (left) lottery			risky (right) lottery			EVL	EVR	EVL–EVR
	high prize	low prize	prob. high prize	high prize	low prize	prob. high prize			
1	5	3	0.1	8.5	0.3	0.1	3.2	1.12	2.08
2	5	3	0.2	8.5	0.3	0.2	3.4	1.94	1.46
3	5	3	0.3	8.5	0.3	0.3	3.6	2.76	0.84
4	5	3	0.4	8.5	0.3	0.4	3.8	3.58	0.22
5	5	3	0.5	8.5	0.3	0.5	4	4.4	-0.4
6	5	3	0.6	8.5	0.3	0.6	4.2	5.22	-1.02
7	5	3	0.7	8.5	0.3	0.7	4.4	6.04	-1.64
8	5	3	0.8	8.5	0.3	0.8	4.6	6.86	-2.26
9	5	3	0.9	8.5	0.3	0.9	4.8	7.68	-2.88
10	5	3	1	8.5	0.3	1	5	8.5	-3.5

Figure 2 – Lottery representation

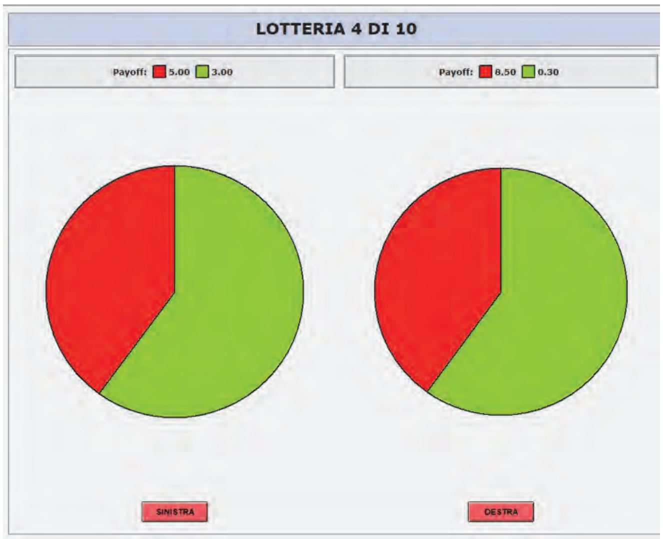


Figure illustrates the user interface of the (Lottery 4) Holt and Laury's protocol. Two lotteries are displayed on the screen. Each prize probability corresponds to a specific colour and this colour assignment is kept throughout all rounds. Subjects are requested to select their preferred lottery by pressing the corresponding button ('left-sinistra' or 'right-destra').

3.4 Feedbacks and payoff

At the end of the experiment the computer randomly draws the return of the portfolio chosen in *Stage III* (based on its expected return and variance).

The results for the Holt and Laury's task are defined as follows. A first lottery is randomly selected among the ten played as the lottery that will be incentivised, while a second lottery is chosen as the lottery that will determine the final payoff (for details see Appendix 1).

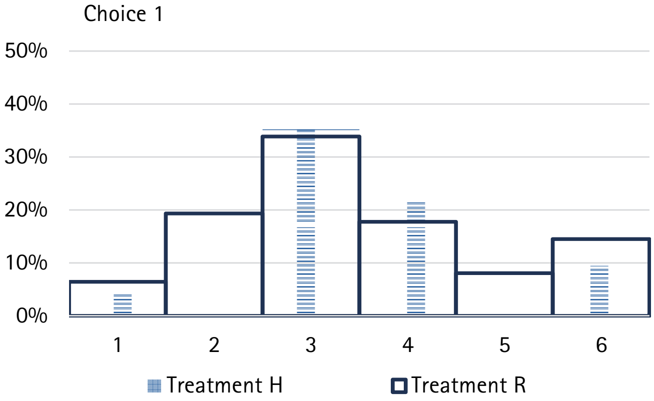
Finally, participants are individually paid, and leave the experiment. The result of each Stage following individual investment and risk choices are privately communicated to participants at the very end of the experiment together with their final payoff in order to avoid that aiming at a certain overall payoff could affect investment decisions through Stages.

4 Results

4.1 The distribution of self-directed and advised choices

The distribution of the self-directed choice (*Choice 1*) made by participants at the beginning of the experiment (*Stage I*) shows no significant difference across treatments (on the basis of a two-tailed p-vale of a two-sample t-test, TSTT henceforth; Figure 3). In other words, subjects assigned respectively to Treatment H and to Treatment R do not significantly differ in their initial risk preferences.

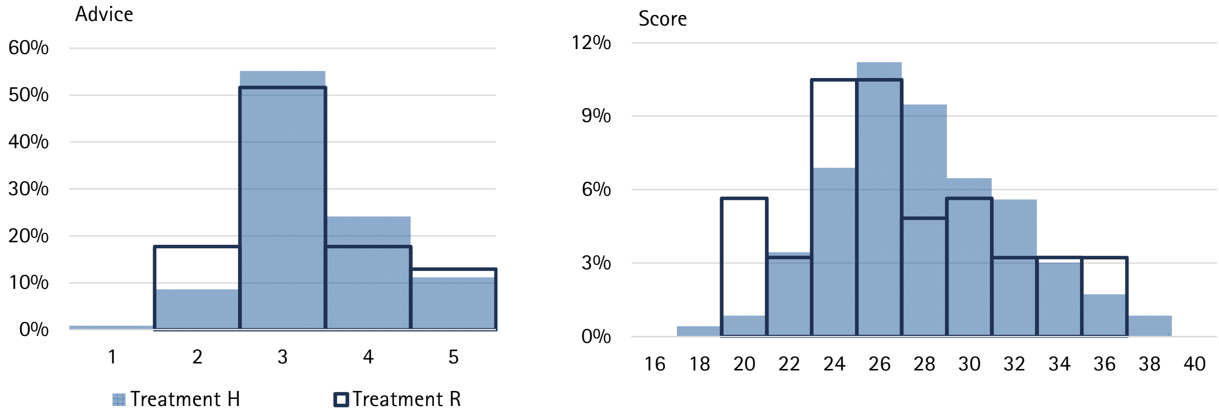
Figure 3 – Self-directed portfolio choice



Notes: TSTT *p*-value=0.789.

The left-hand side of Figure 4 depicts the distribution of the portfolios that were recommended (*Advice*) on the basis of the participants' risk profile, as stemming for the Grable&Lyttle Quiz, and finds no significant difference across treatments (on the basis of the TSTT). The right-hand side of Figure 4 shows the distribution of the scores resulting from the Grable&Lyttle questionnaire (*Score*) which are also not-significantly different (as shown by the TSTT, although the average score is slightly higher for treatment H). Given the lack of difference in *Choice 1* across treatments, it is not surprising that the questionnaire score as well as the advice given are also homogeneously distributed across treatments. Still, this evidence indicates robustness and consistency of both the risk elicitation methods used (the self-directed portfolio choice and the questionnaire).

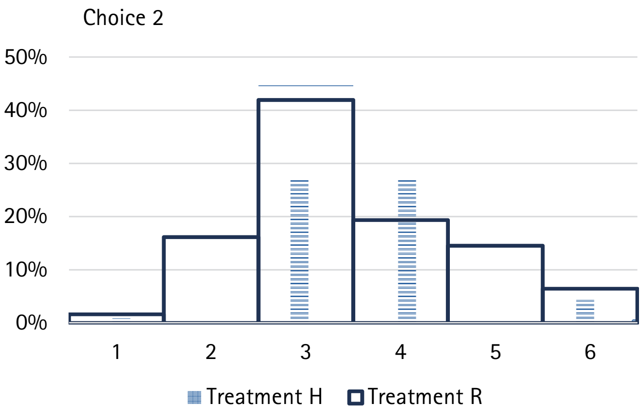
Figure 4 – Questionnaire results and portfolio advice



Notes: TSTT *p*-value=0.440 for the advice (left panel); TSTT *p*-value=0126 for the score (right panel).

As for the investment decision made after having received the advice (*Choice 2* or 'advised portfolio choice'), Figure 5 shows that the distribution of the advised portfolio choices is similar across the two groups receiving the recommendation respectively from a human advisor and a robo advisor (p=0.8395 using TSTT).

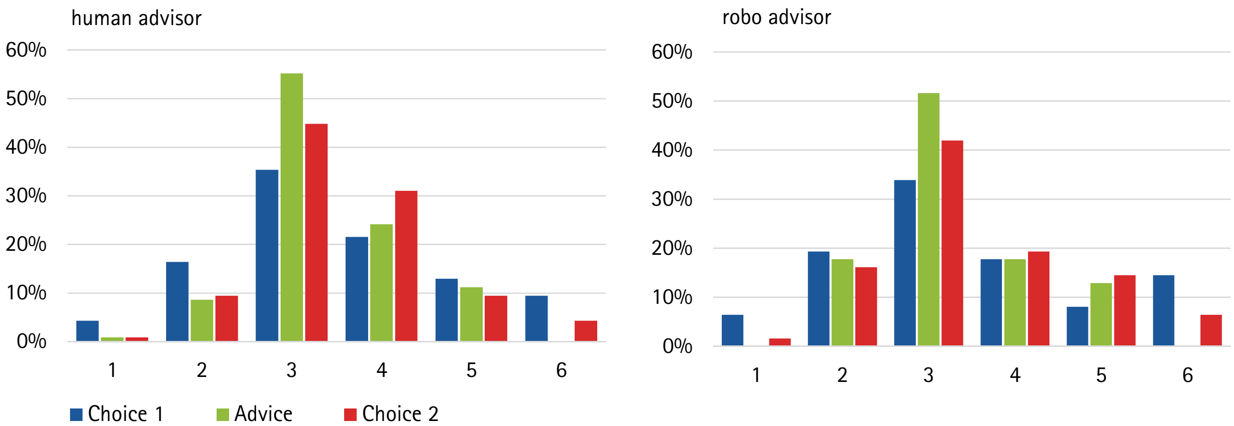
Figure 5 – Advised portfolio choice



Notes: TSTT *p*-value=0.840.

Figure 6 depicts both self-directed (*Choice 1*) and advised (*Choice 2*) investment decisions and the advice given by the human (left panel) and the robo (right panel) advisors. Overall, it shows no large difference between the two treatments, indicating that no strong effect is associated with the source of the advice received by participants. Interestingly, in both treatments there are a few participants autonomously choosing the riskiest portfolio (Portfolio 6) that stick to their decision even after being advised a safer portfolio.

Figure 6 - Share of portfolio choices



In order to study possible treatment effects, we look at the individual mismatch between the two investment decisions made during the experiment (*Choice 1* and *Choice 2*) and the advice received. For that purpose, we created the following variables:

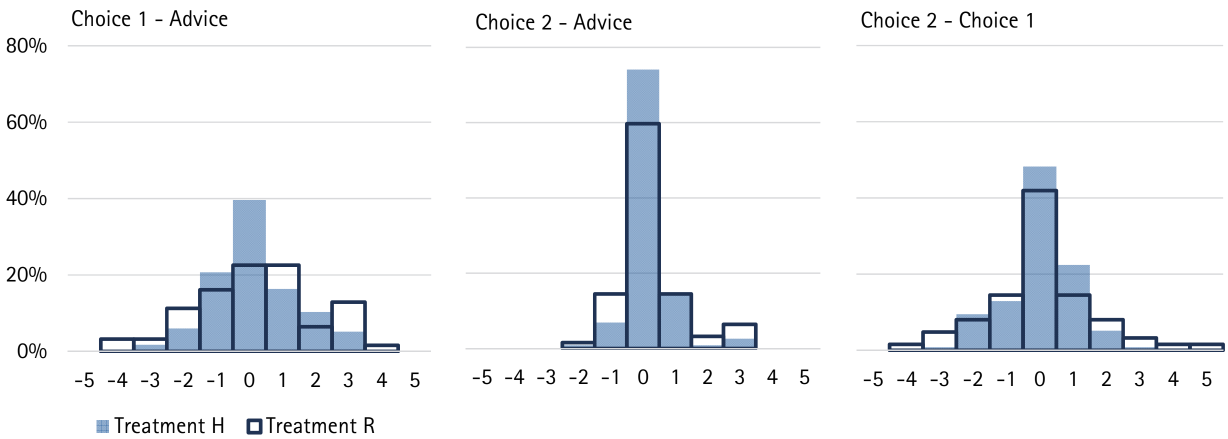
i. *Choice 1 - Advice = self-directed choice - advice received*, indicating whether participants are making their self-directed choice according to their risk preferences (as revealed by the questionnaire);

ii. *Choice 2 - Advice = advised choice - advice received*, capturing the willingness to follow the advice received from the advisor;

iii. *Choice 2 – Choice 1 = advised - self-directed choice*, verifying the individual consistency across choices.

Figure 7 shows the distribution differences across treatments. It is interesting to note that in *Treatment H*, *Choice 1* coincides with the advice received in 40% of the cases, whereas this occurs only in 20% of the cases in *Treatment R* (see the top-left panel). As for the advice received, it is more frequently followed by subjects in *Treatment H* than subjects in *Treatment R* (see the top-right panel): such evidence is consistent with our main result about the higher propensity to follow the advice when it confirms the self-directed portfolio decision the investor would have made (see next section for econometric results). On statistical grounds, however, none of the three differences depicted in Figure 7 are significantly different between the two treatments (see two sample t-test probabilities).

Figure 7 – Decision adjustments



Notes: TSTT *p*-value=0.843 for *Choice 1 – Advice* (left panel); TSTT *p*-value=0.907 for *Choice 2 – Advice* (central panel); TSTT *p*-value=0.587 for *Choice 2 – Choice 1* (right panel).

In order to analyse the probability to follow the advice as a function of game-related characteristics (i.e. treatment, advice and choice variables), we run a probit regression of three model specifications where the dependent variable is *D(Choice 2=Advice)*, a dummy taking value 1 when the advised choice is equal to the advice received (Table 4). From Model 1 to Model 3 the dependent variable is regressed over treatment, *D(Choice 1=Advice)*, *Choice 1* and the *Advice*. Overall, the probability to follow the advice mainly depends on whether the participant has correctly identified the suitable portfolio based on her/his risk preferences at the beginning of the experiment (see Model 1). We then control for the level of self-directed choice and the advice only (Model 2); the latter is a broad measure of taste for risky choice and we find that treatment is statistically significant. When participants are correctly identifying their optimal profile, treatment becomes irrelevant as well as the choice's levels (Model 3).

In this sense, we consider only the players failing to correctly identify their optimal portfolio in the self-directed choice (Model 4) for whom we find that treatment is significant: when the self-directed choice is different from the later suggestion, we find that participants are more willing to follow the human rather than robo advice.

Table 4 – Marginal effects of probit regression analysis

	Model specification			
	Model 1 *dydx/se*	*Model 2* *dydx/se*	*Model 3* *dydx/se*	*Model 4* *dydx/se*
Treatment R	-0.071	-0.141**	-0.066	-0.149*
	(-0.062)	(-0.069)	(-0.063)	(-0.089)
D(Choice 1=Advice)	0.389***		0.404***	
	(-0.069)		(-0.067)	
Choice 1		-0.026	0	-0.013
		(-0.027)	(-0.023)	(-0.03)
Advice		0.008	0.041	
		(-0.041)	(-0.038)	
N	178	178	178	118
χ^2(pval)	0.121	0.008	0.276	0.278

Notes: Dependent variable: D(*Choice 2=Advice*) = 1 if the advice is followed; 0 otherwise. For each covariate we report both *dydx* (= average marginal effects) and *se* (= standard errors with * p<0.1; ** p<.05; ***p<.01) from probit estimations. We report the *p*-value from the Pearson χ^2 goodness-of-fit test for the fitted model in the last row of the table ($\chi^2(pval)$); the null hypothesis assumes that the model properly fits the observed variables.

4.2 Portfolio decisions and individual characteristics

The next step is to test whether the portfolio decisions are correlated with the other variables collected in the experiment, that is risk attitude, digital literacy, financial literacy and socio-demographic characteristics of the participants. Indeed, we do not focus specifically on the socio-economics characteristics of the subjects joining the experiment as they are quite homogeneous in age and education track.

Based on the experimental design, we have collected three measures directly related to each participant's risk perception: the initial portfolio choice, the questionnaire underpinning the financial advice, and the lottery task at the end of the experimental session.

For the post-experimental lottery task we consider three indicators to describe the participant's behaviour, delivering similar information but with some differences:

a. the average number of risk lotteries chosen (*risk id* hereafter); this can be read as the probability to choose the risky option (without considering a specific coefficient or model identifying the risk): participants with a larger index are, overall, more willing to take risk;

b. the (first) switching point, where the participant moved from the 'safe' lottery choice to the 'risky' one (*firstswitch* hereafter), regarded as an ordinal variable: larger values are associated to an increasing level of risk aversion;[16]

c. The average Sharpe ratio difference between each pair of lotteries (*delta id*): higher values of the Sharpe ratio indicate increasing risk aversion.[17]

Table 5 shows the correlation among the different risk measures collected: all measures are increasing in the willingness to take risk, except *risk id* and *delta id*, which show negative correlations. The Advice is correlated significantly to all the measures of risk, when considering both the lotteries and the portfolio choices. We can therefore conclude that the *Advice*, based on the questionnaire score, reflects the willingness to take risk quite well. The correlation with *Choice 1* and lottery measures is not significant whereas *Choice 2* shows a higher correlation to risk propensity in lotteries (nonetheless the coefficients are not significant).

Table 5 – Pairwise correlations and significance level for risk preference measures

	risk id	firstswitch	delta id	Choice 1	Choice 2	Advice
risk id	1.000					
firstswitch	-0.794	1.000				
	0.000					
delta id	-0.993	0.775	1.000			
	0.000	0.000				
Choice 1	0.042	0.005	-0.054	1.000		
	0.576	0.946	0.473			
Choice 2	0.106	-0.033	-0.114	0.455	1.000	
	0.160	0.659	0.130	0.000		
Advice	0.241	-0.202	-0.238	0.141	0.639	1.000
	0.001	0.007	0.001	0.061	0.000	

Notes: For each variable we report correlation and significance level.

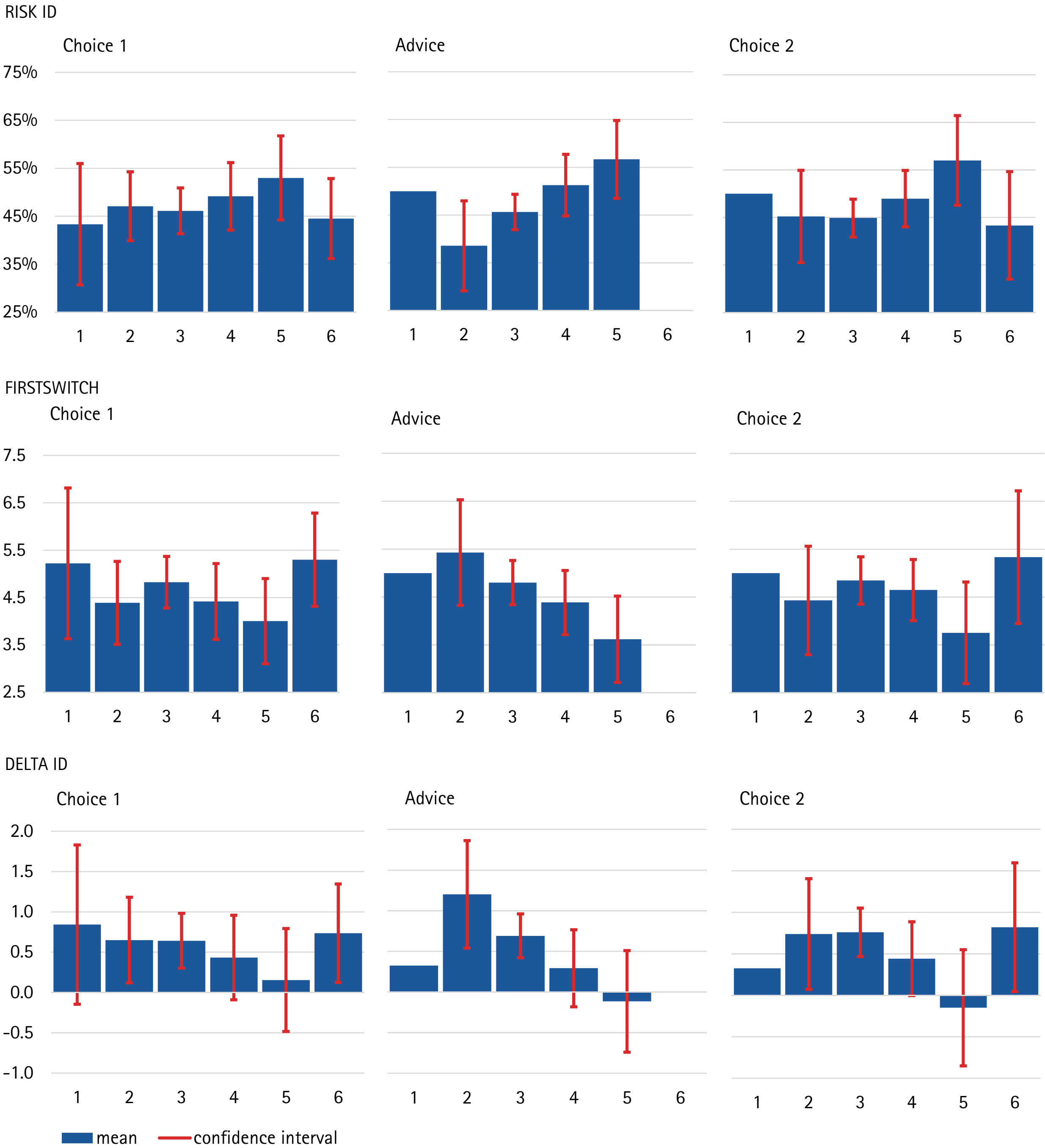
We present such correlation in Figure 8, where the top three graphs consider the correlation between *risk id* and *Choice 1*, Advice, and *Choice 2*, respectively. Overall, the advice received by participant is well correlated with risky choices in the lotteries (we disregard the first bar, counting for only one observation),

16 As already mentioned, following the Holt and Laury (2002) protocol, subjects are presented with a menu of choices; choosing between all lottery pairs permits measurement of the degree of risk aversion, and also estimation of its functional form. By assuming a specific model of risk preferences (such as Constant Relative Risk Aversion, CRRA), the function assigns a (range) value to the risk propensity when the switch from the safe to the risk lottery occurs. Risk lovers are switching between the first four lotteries, risk neutral are supposed to switch between lottery 4 and 5 and risk averse switches to the risky option after lottery 5. In the present study we do not assume a specific model of risk preferences, and consider the switching point as an ordinal variable.

17 The Sharpe ratio is computed as the ratio between the expected value and the standard deviation of each lottery; we calculate the difference between the coefficient of variation of the chosen lottery minus the not chosen lottery and then averaged by subject.

whereas the self-directed and advised choices on the portfolio do not correlate with the lottery choice. Similar conclusions can be drawn for the central figures (focusing on *firstswitch*) and the bottom figures (focusing on *delta id*). We therefore conclude that the questionnaire and the lotteries show a robust correlation with individuals' risk attitude, while the self-directed portfolio decisions are related to other factors besides risk preferences.

Figure 8 – Bar plots of risk measures by portfolio allocation of Choice 1, Advice and Choice 2



In addition to the strong and expected correlation between the portfolio choices and the risk preferences, we test the correlation between the (financial and digital) literacy of participants and their portfolio investment decisions, both prior to as well as after receiving the advice from the advisor (*Choice 1* and *Choice 2*).

The financial literacy (*Financial lit.*) test outputs an indicator from 0 to 5, with 0 being the lowest and 5 the highest possible score. The test included 5 questions with a unique correct answer. A refusal to answer could be considered as a proxy for both lack of knowledge as well as impatience (*flPNA*).

The digital literacy (*Digital lit.*) test is based on a question about self-assessed familiarity with some basic concepts: the indicator goes from 1 to 5, with 1 representing the lowest and 5 the highest digital literacy.

Finally, we take into account the individual perception of how financially competent they think they are (*self-assessed financial lit.*); the value goes from 1 to 10.

Table 6 – Pairwise correlations and the significance level for literacy

	digital lit.	financial lit.	flPNA	self-assessed financial lit.	Choice 1	Choice 2	Advice
digital lit.	1.000						
financial lit.	0.078	1.000					
	0.301						
flPNA	0.024	-0.263	1.000				
	0.749	0.000					
self-assessed financial lit.	0.306	0.293	0.009	1.000			
	0.000	0.000	0.905				
Choice 1	0.113	-0.030	0.074	0.117	1.000		
	0.134	0.687	0.323	0.119			
Choice 2	0.153	0.146	0.057	0.297	0.455	1.000	
	0.041	0.052	0.453	0.000	0.000		
Advice	0.135	0.190	-0.017	0.299	0.141	0.639	1.000
	0.072	0.011	0.819	0.000	0.061	0.000	

Notes: For each variable we report correlation and significance level.

Table 6 shows that the self-directed choice (*Choice 1*) is not correlated to any literacy or self-assessed financial literacy. *Choice 2* is weakly correlated to financial literacy and digital literacy but strongly correlated to individual self-assessed financial literacy, signalling that increasing levels of knowledge (actual and self-assessed) are associated to riskier portfolio choices.

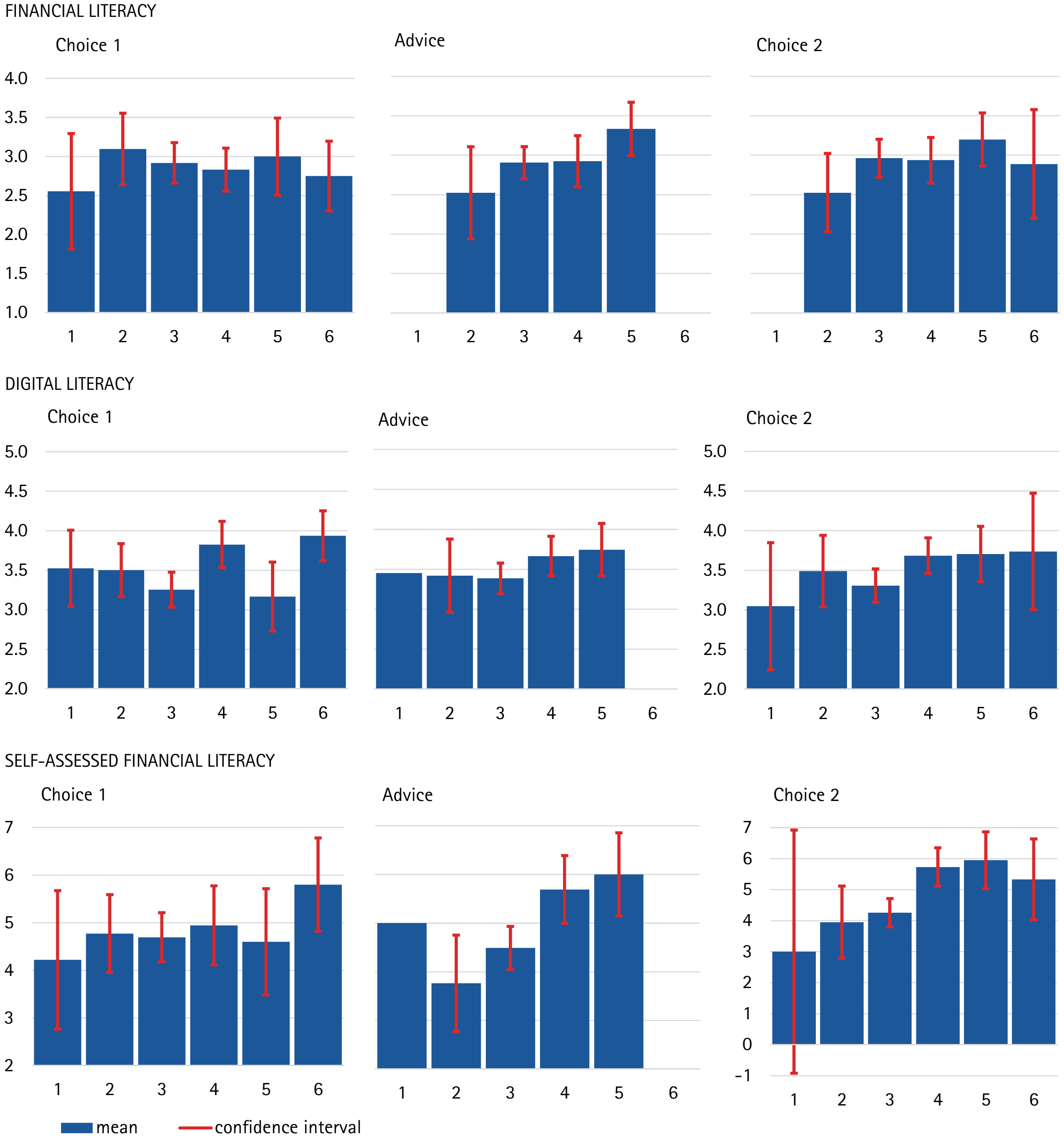
We also check if digital literacy, financial literacy and self-assessed financial literacy correlate to risk preferences from the lottery allocations and we observe that increasing digital literacy is associated to increasing risk aversion while self-assessed financial literacy is significantly correlated to risk loving profiles (see Table 7).

Table 7 – Pairwise correlations between number of risky choices in the lotteries and literacy

	digital lit.	financial lit.	fIPNA	self-assessed financial lit.
risk id	-0.071	0.007	-0.101	0.075
	0.003	0.777	0.000	0.002

Notes: For each variable we report correlation and significance level.

Figure 9 – Bar plots of literacy and self-assessed financial literacy measures by portfolio allocation of Choice 1, Advice and Choice 2

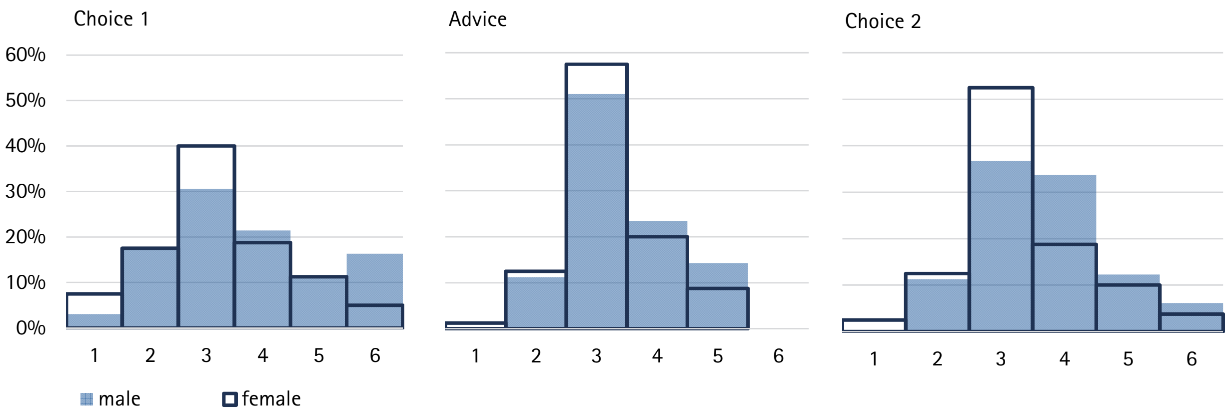


Finally, the correlations between the portfolio allocations and financial literacy, digital literacy and self-assessed financial literacy are represented in Figure 9 (in the top, in the centre and in the bottom part of the Figure, respectively). We do not find significant and relevant differences between portfolio's levels (see the wide intervals of confidence), nevertheless Financial lit. is increasing when the portfolio suggested is riskier (*Advice*). Similar correlation characterises digital literacy and self-assessed financial literacy.

4.3 The heterogeneity analysis

We next look at gender differences in both self-directed portfolio choices and the advice received after the questionnaire. In line with prior literature (Charness and Gneezy, 2012; Eckel and Grosmann, 2002; Merrill Lynch, 1996), our results indicate that men are significantly more likely to select a riskier portfolio, both before and after receiving the advice, than women are. On the other hand, given our experimental design, the recommendation given by the human advisors couldn't be gender biased; therefore the advice delivered to participants is not significantly different across men and women[18] (Figure 10 in the centre). This indicates that the portfolio decision and the risk-profiling questionnaire do not capture the same effects in both genders: overall, it seems that men do not exhibit the risk seeking behaviour underlined in the above mentioned studies and exhibited in *Choice 1* and *Choice 2*.

Figure 10 – Distribution of choices by gender



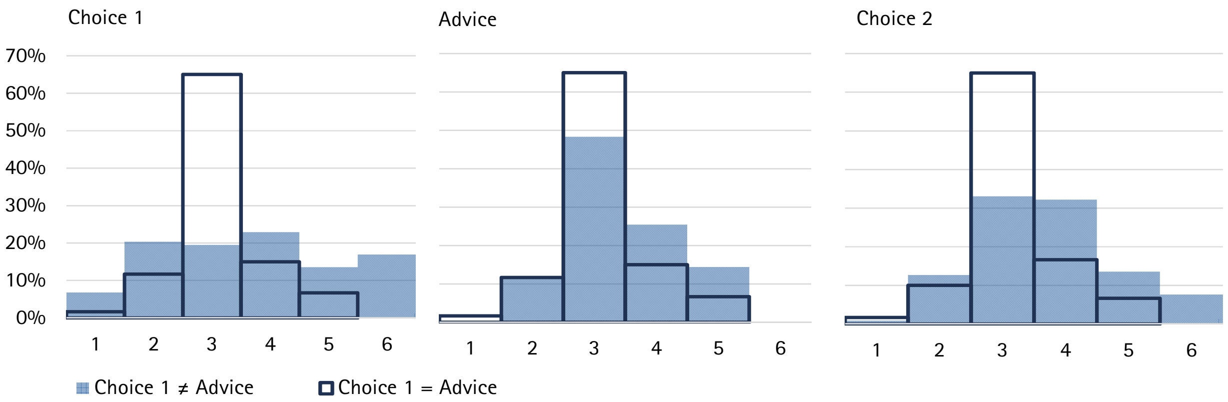
Notes: TSTT *p*-value=0.024 for *Choice 1* (left panel); TSTT *p*-value=0.155 for *Advice* (central panel); TSTT *p*-value=0.036 for *Choice 2* (right panel).

Figure 11 again depicts both portfolio choices, as well as the advice received separately for those participants whose *Choice 1* matches the advice received and those whose choice doesn't match the advice. While it should not be surprising that we find that the distributions of these two groups are quite different, what is interesting is both how many participants *Choice 1* doesn't match the advice they received (66% of participants) as well as to what extent the distribution varies for

18 We also find no significant difference if we compare directly the questionnaire scores on which the advice is based on.

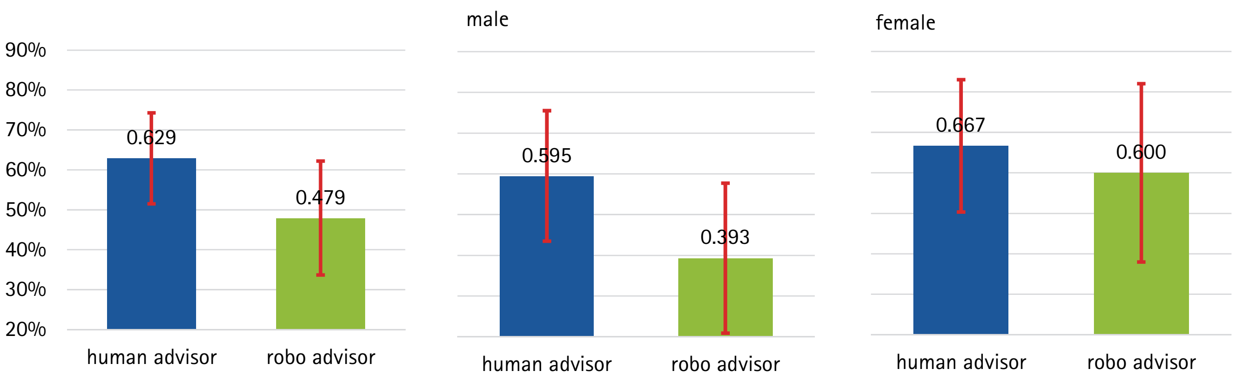
those whose choice doesn't match. Further, the rightmost panel of Figure 9 indicates that participants whose *Choice 1* and advice received didn't match on average do move in the direction of the advice.

Figure 11 – Distribution of choices by self-directed choice matching the advice



A large portion (34%) of participants who selected the same portfolio in *Choice 1* which was later recommended to them had no possibility to move their portfolio choice to the recommended one. Figure 12 therefore focuses only on the participants whose *Choice 1* was different from advice received and depicts any gender and treatment effects for $Choice\ 1 \neq Advice$ participants.

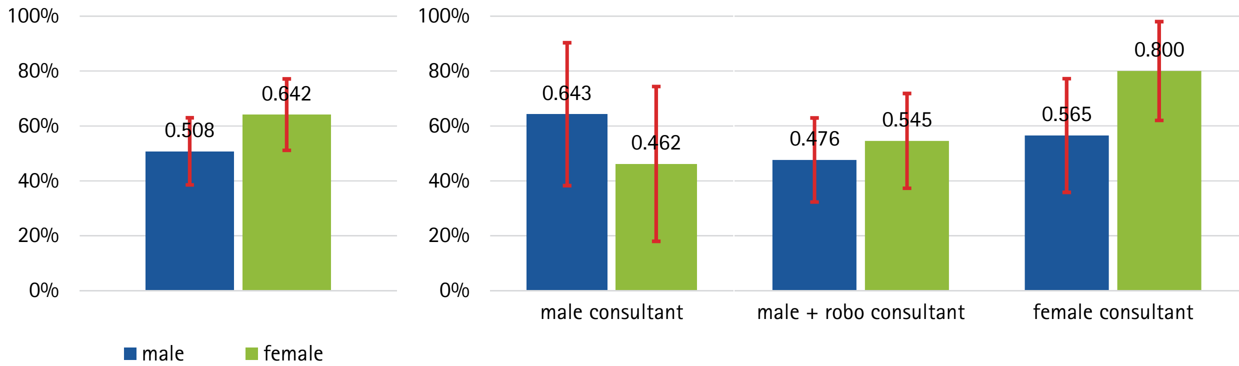
Figure 12 – Probability to follow the suggestion D(Choice 2=Advice) when Choice 1≠Advice, by treatment and gender



Notes: TSTT *p*-value=0.109 (left panel); TSTT *p*-value=0.110 (central panel); TSTT *p*-value=0.632 (right panel).

The left side of Figure 12 shows that $Choice\ 1 \neq Advice$ participants seem to follow human advice more often. This result is, however, just short of marginally significant using a two-tailed t-test. The right side of Figure 12 further splits the $Choice\ 1 \neq Advice$ participants by gender and indicates that the difference in following the two sources of advice mainly comes from male participants. Namely, men seem to follow human advisors more than robo-ones, whereas the females follow both types of advisors similarly (and more frequently). Again this result is just short of being statistically significant and is not confirmed by econometric analysis (see next section).

Figure 13 – Probability to follow the suggestion D(Choice 2=Advice) when Choice 1≠Advice, by gender constellation



Finally, Figure 13 represents the probability to follow the advice by gender (left side); overall female participants tend to follow more frequently the advice received, but the difference is not significant. The right panel focuses on the gender of the participant as well as the gender of advisor. By looking at the gender constellation we do not find significant differences, but women tend to trust more the female advisor whereas men seem disregard very often the suggestion of the female advisor.

5 Estimation models

The present section focuses on the estimation models aimed at gathering evidence on our main research question that, as already mentioned, concerns whether a financial recommendation is trusted more (or less) when received from a robo advisor as opposed to a human advisor.

We therefore model the probability to follow the advice ($D(Choice\ 2 = Advice)$) as a function of the source of the advice itself (*Treatment R*, equal to 1 if the source is the robo advisor and 0 otherwise). In addition, we consider the following control variables: a dummy variable ($D(Choice\ 1 = Advice)$) equal to 1 if the self-directed choice is equal to the advice received and 0 otherwise, i.e. equal to 1 if the individual correctly predicted his/her investment profile as stemming from the Grable&Lytton Quiz; a set of demographic characteristics (*Z*); four personal characteristics/skills (*X*), that may affect individual attitudes towards a digital advisor, such as participant's financial literacy, digital literacy, risk aversion and self-perceived financial knowledge. For each of these four control variables of interest (X), we present four different models, all having as dependent variable the decision to follow the advice ($D(Choice\ 2 = Advice)$):

i. Model 1 (M1) controls only for the source of the advice, the subject being aware of her or his investment profile *D(Choice 1=Advice)* and the control variable of interest;

ii. Model 2 (M2) adds to Model 1 a set of demographic characteristics (*Z*), i.e. gender, age and whether the student is enrolled in the Economics course;

iii. Model 3 (M3) runs M2 for a restricted sample, including only those subjects who were not able to correctly estimate their investment profile, i.e. those who took a self-directed choice different from the advice received;

iv. Model 4 (M4) adds the information on the gender of the advisor, and therefore is only performed on the sample of participants assigned to *Treatment H*.

The model specification is therefore the following:

$$D(Choice\ 2 = Advice)_{i,t} = \alpha + \beta_1 TreatmentR_i + \beta_2 D(Choice\ 1 = Advice)_{i,t} + \beta_3 X_i + \beta_4 Z_i + \epsilon_{i,t}$$

All the 16 specifications are estimated via a probit regression with robust standard errors. Table 8 to Table 11 report the estimates of the marginal effects of each model. In all specifications reference categories are male participants and non-Economics students; reference category for Treatment in models 1 to 3 is Human advisor. In Table 12, the estimates for models 1 to 4 are reported with the full set of control variables used together.

Our main results are illustrated in the following.

When the full sample is considered, participants do not show any propensity towards a specific type of advice, i.e. the probability to follow the advice does not depend on whether they meet a human advisor or face an algorithm.

The main driver of the probability to follow the advice is the alignment between the self-directed choice (made at *Stage I* of the experiment) and the advice received (at *Stage II*). In other words, the probability to follow the advisor (either human or robo) increases if the recommendation confirms individual's own beliefs about her/his investor profile. This result might be explained by referring to individuals' natural tendency to selectively listen to people (or rely on sources of information, in general) that confirm their prior ideas or values (the so called 'confirmation bias'; Cerulli Associates and Charles Schwab Investment Management, 2019; Cheng, 2019; Golman et al., 2017; Rigoni, 2016).

On the other hand, when the self-directed choice does not coincide with the advice, the source of the advice does play a role (Model 3). In this case participants, who are supposed to have not been able to correctly assess their risk profile, are more likely to follow the recommendation received from a human advisor and less likely to follow the advice received from an algorithm. Although this result is robust to the four control variables (financial literacy, digital literacy, risk aversion and confidence in one's own financial knowledge), it is proved on a sample consistently smaller than the full sample of participants and deserves further investigation.

Table 8 – Marginal effects of all models with financial literacy as control variable of interest

	Model specification			
	Model 1 *dydx/se*	*Model 2* *dydx/se*	*Model 3* *dydx/se*	*Model 4* *dydx/se*
Treatment R	-0.070	-0.100	-0.185**	
	(0.065)	(0.064)	(0.087)	
D(Choice 1=Advice)	0.354***	0.347***		0.293***
	(0.057)	(0.057)		(0.079)
financial lit.	-0.010	0.000	0.000	0.01
	(0.034)	(0.034)	(0.044)	(0.039)
female		0.030	0.100	0.020
		(0.065)	(0.090)	(0.075)
age		0.020	0.020	0.020
		(0.012)	(0.018)	(0.016)
economics		-0.110	-0.150	-0.030
		(0.069)	(0.100)	(0.087)
female advisor				0.060
				(0.074)
N	178	178	118	116
χ^2(pval)	0.094	0.376	0.504	0.360

Notes: Dependent variable: D(*Choice 2=Advice*) = 1 if the advice is followed; 0 otherwise. For each covariate we report both *dydx* (= average marginal effects) and *se* (= standard errors with * p<0.1; ** p<.05; ***p<.01) from probit estimations. We report the *p*-value from the Pearson χ^2 goodness-of-fit test for the fitted model in the last row of the table ($\chi^2(pval)$); the null hypothesis assumes that the model properly fits the observed variables.

Table 9 – Marginal effects of all models with digital literacy as control variable of interest

	Model specification			
	Model 1 *dydx/se*	*Model 2* *dydx/se*	*Model 3* *dydx/se*	*Model 4* *dydx/se*
Treatment R	-0.08	-0.1	-0.190**	
	(0.065)	(0.063)	(0.087)	
D(Choice1=Advice)	0.360***	0.353***		0.291***
	(0.057)	(0.057)		(0.080)
digital lit.	0.04	0.04	0.093*	0.01
	(0.036)	(0.036)	(0.048)	(0.044)
female		0.05	0.14	0.03
		(0.064)	(0.089)	(0.075)
age		0.02	0.02	0.02
		(0.013)	(0.018)	(0.016)
economics		-0.116*	-0.13	-0.02
		(0.069)	(0.097)	(0.087)
female advisor				0.06
				(0.076)
N	178	178	118	116
χ^2(pval)	0.781	0.152	0.293	0.370

Notes: Dependent variable: D(*Choice 2=Advice*) = 1 if the advice is followed; 0 otherwise. For each covariate we report both *dydx* (= average marginal effects) and *se* (= standard errors with * p<0.1; ** p<.05; ***p<.01) from probit estimations. We report the *p*-value from the Pearson χ^2 goodness-of-fit test for the fitted model in the last row of the table ($\chi^2(pval)$); the null hypothesis assumes that the model properly fits the observed variables.

Table 10 – Marginal effects of all models with risk aversion as control variable of interest

	Model specification			
	Model 1 *dydx/se*	*Model 2* *dydx/se*	*Model 3* *dydx/se*	*Model 4* *dydx/se*
Treatment R	-0.07	-0.1	-0.188**	
	(0.066)	(0.065)	(0.089)	
D(Choice 1=Advice)	0.356***	0.348***		0.303***
	(0.056)	(0.056)		(0.075)
risk id	0.08	0.09	-0.05	0.34
	(0.170)	(0.162)	(0.218)	(0.210)
female		0.03	0.1	0.000
		(0.064)	(0.090)	(0.076)
age		0.02	0.02	0.02
		(0.013)	(0.018)	(0.016)
economics		-0.120*	-0.14	-0.04
		(0.070)	(0.099)	(0.085)
female advisor				0.07
				(0.074)
N	178	178	118	116
χ^2(pval)	0.158	0.206	0.416	0.395

Notes: Dependent variable: D(*Choice 2=Advice*) = 1 if the advice is followed; 0 otherwise. For each covariate we report both dydx (= average marginal effects) and se (= standard errors with * p<0.1; ** p<.05; ***p<.01) from probit estimations. We report the p-value from the Pearson χ^2 goodness-of-fit test for the fitted model in the last row of the table ($\chi^2(pval)$); the null hypothesis assumes that the model properly fits the observed variables.

Table 11 – Marginal effects of all models with self-assessed financial literacy as control variable of interest

	Model specification			
	Model 1 *dydx/se*	*Model 2* *dydx/se*	*Model 3* *dydx/se*	*Model 4* *dydx/se*
Treatment R	-0.07	-0.1	-0.178**	
	(0.064)	(0.064)	(0.088)	
D(Choice 1=Advice)	0.358***	0.351***		0.302***
	(0.057)	(0.056)		(0.081)
self-assessed financial lit.	-0.02	-0.02	-0.02	-0.02
	(0.014)	(0.016)	(0.023)	(0.019)
female		0.01	0.06	0.000
		(0.065)	(0.094)	(0.075)
age		0.02	0.03	0.028*
		(0.013)	(0.019)	(0.016)
economics		-0.08	-0.09	0.01
		(0.078)	(0.112)	(0.096)
female advisor				0.05
				(0.076)
N	178	178	118	116
χ^2(pval)	0.086	0.259	0.246	0.273

Notes: Dependent variable: D(*Choice 2=Advice*)= 1 if the advice is followed; 0 otherwise. For each covariate we report both *dydx* (= average marginal effects) and *se* (= standard errors with * p<0.1; ** p<.05; ***p<.01) from probit estimations. We report the *p*-value from the Pearson χ^2 goodness-of-fit test for the fitted model in the last row of the table ($\chi^2(pval)$); the null hypothesis assumes that the model properly fits the observed variables.

Table 12 - Models 1 to 4 with the full set of control of interest

	Model specification			
	Model 1 *dydx/se*	*Model 2* *dydx/se*	*Model 3* *dydx/se*	*Model 4* *dydx/se*
Treatment R	-0.06	-0.09	-0.176**	
	(0.065)	(0.064)	(0.089)	
D(Choice 1=Advice)	0.372***	0.363***		0.323***
	(0.056)	(0.056)		(0.078)
financial lit.	0.01	0.01	0.000	0.01
	(0.036)	(0.035)	(0.046)	(0.038)
digital lit.	0.062*	0.05	0.114**	0.02
	(0.037)	(0.038)	(0.051)	(0.043)
risk id	0.15	0.13	0.01	0.35
	(0.168)	(0.163)	(0.225)	(0.219)
self-assessed financial lit.	-0.031*	-0.02	-0.04	-0.02
	(0.016)	(0.018)	(0.023)	(0.020)
female		0.02	0.1	-0.02
		(0.065)	(0.090)	(0.079)
age		0.02	0.03	0.02
		(0.013)	(0.018)	(0.016)
economics		-0.07	-0.05	0.000
		(0.079)	(0.108)	(0.096)
female advisor				0.07
				(0.072)
N	178	178	118	116
X^2(pval)	0.054	0.136	0.165	0.332

Notes: Dependent variable: D(Choice 2=Advice)= 1 if the advice is followed; 0 otherwise. For each covariate we report both *dydx* (= average marginal effects) and *se* (= standard errors with * p<0.1; ** p<.05; ***p<.01) from probit estimations. We report the *p*-value from the Pearson χ^2 goodness-of-fit test for the fitted model in the last row of the table ($\chi^2(pval)$); the null hypothesis assumes that the model properly fits the observed variables.

Neither the gender of the participant nor the attendance of the Economics course do affect the probability to follow the advice received. In addition, the main result on the non-relevance of the source of the advice is robust across the four specifications including individuals' characteristics X, i.e. it is not affected by participant's levels of financial or digital literacy, risk aversion or self-assessed financial knowledge.[19]

When the subset of participants of model M3 is considered and all controls are included, participants with a higher level of digital literacy show a higher probability to follow the advice (both human and robo; Table 12).[20]

19 The result holds also when interacting the treatment variable with each control variable.

20 It is well known that digital literacy might result to be a key driver in the propensity to rely on robo advice and on digital financial services in general. For instance, Caratelli et al. (2019) find that individuals' cultural attitude towards innovation is key in shaping investors' attitudes towards automated advice. In addition, digital literacy does not necessarily go hand in hand with financial knowledge, as shown by empirical evidence relating both adults and youth population (OECD, 2017, 2018 and 2020). Nonetheless, as mentioned above, participants in our experiment,

The gender of the (human) advisor does not play a role on the probability that participants follow the advice. Nonetheless, in order to deeply investigate the interaction between the gender of the advisor and that of the participants, we carried out the gender constellation (see next section).

Table 13 – Marginal effects of Model 4 with control variables of interest (both separated and all together) and gender constellation

	Model specification				
	FinLit *dydx/se*	*DigLit* *dydx/se*	*RiskAtt* *dydx/se*	*Confid* *dydx/se*	*Full* *dydx/se*
D(Choice 1=Advice)	0.268***	0.267***	0.274***	0.271***	0.289***
	(0.072)	(0.072)	(0.068)	(0.074)	(0.071)
age	0.02	0.02	0.02	0.03	0.02
	(0.015)	(0.015)	(0.015)	(0.016)	(0.016)
economics	-0.02	-0.02	-0.03	0.01	0.000
	(0.082)	(0.081)	(0.079)	(0.093)	(0.090)
financial lit.	0.01				0.02
	(0.036)				(0.035)
digital lit.		0.03			0.04
		(0.042)			(0.041)
risk id			0.336*		0.354*
			(0.195)		(0.201)
self-assessed financial lit.				-0.01	-0.01
				(0.018)	(0.019)
(Baseline: partFconsF)					
partFconsM	-0.222**	-0.227**	-0.230**	-0.210**	-0.235**
	(0.102)	(0.102)	(0.098)	(0.105)	(0.099)
partMconsF	-0.164*	-0.185**	-0.14	-0.15	-0.15
	(0.093)	(0.094)	(0.094)	(0.098)	(0.101)
partMconsM	-0.06	-0.07	-0.05	-0.04	-0.05
	(0.103)	(0.101)	(0.101)	(0.102)	(0.102)
N	116	116	116	116	116
χ^2(pval)	0.394	0.363	0.519	0.285	0.511

Notes: Dependent variable: D(*Choice 2=Advice*) = 1 if the advice is followed; 0 otherwise. For each covariate we report both *dydx* (= average marginal effects) and *se* (= standard errors with * p<0.1; ** p<.05; ***p<.01) from probit estimations. We report the *p*-value from the Pearson χ^2 goodness-of-fit test for the fitted model in the last row of the table ($\chi^2(pval)$); the null hypothesis assumes that the model properly fits the observed variables. The reference group, omitted in the regression, is female participant (partF) taking advice from the female consultant (consF). We compare the baseline group with the other possible interactions (i) female participant advised by a male consultant, (ii) male participant advised by a female advisor, and (iii) a male consultant meeting with a male participant. Fit measures will be available before publication.

were all students exhibiting low variability in critical characteristics such as financial and digital literacy. A different sample showing a higher heterogeneity in such variables might have provided different results about the role of these factors. However, the planned follow-up of the experiment, engaging also senior individuals and real investors, unfortunately was cancelled due to limitations linked to Covid-19 pandemic.

5.1 Gender constellation

In order to verify whether the gender of the human advisor enters differently in the decision of female and male participants to follow the advice received, we replicate Model 4 by including separately our four control variables *X* and control for the gender constellation. To replicate the robustness check performed in Table 12, we also report the results for the 'full' specification, including all control variables together. Table 13 reports the marginal effects of a probit model with robust standard errors, with female participant and female advisor being the reference category for the gender constellation.

Our results show that:

i. women are more likely to follow the advice provided by a female advisor, compared to the advice given by a male advisor and such evidence is strong and robust to all our control variable of interest;[21]

ii. men are less likely to follow the advice provided by a female advisor compared to female participants (the significance of this result is weaker when compared to our main result, i.e. the probability to follow the advice does not depend on whether they met a human advisor or faced an algorithm).

21 Such a result is consistent with a recent research from State Street Global Advisors showing that 55% of women between ages 25 and 34 prefer working with female advisors. It also finds that women using female advisors are more confident in their advisor's investing skills, and more likely to say their advisor has their best interest in mind and at heart (Avery, 2016)

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Appendix 1

Instructions

Rome, October 2018

Welcome. This is an experiment on how individuals make some decisions. Pay attention to how you make your decisions and the answers you give as they will determine the payoff you will get from the experiment, that will be settled immediately and in cash at the end of the experiment.

Your answers and results for the experiment will be treated anonymously and exclusively for scientific research purposes.

This experiment consists of three phases. You will receive instructions for each phase before starting it.

Your decisions and responses are individual and therefore we recommend that you do not communicate with other participants during the experiment. Those who violate this rule will be excluded from the experiment without receiving any payment. In this experiment, you will earn experimental tokens: each experimental token is converted to the following rate: (1 experimental token = €0.02).

At the end of reading the instructions you will have a few minutes to read them again. if something is not clear please raise your hand and remain silent, one of the experimenters will come to help you individually. In any case, the computer will guide you through the different phases of the experiment.

We recommend that you take note of the number that identifies you that will accompany you in the various phases of the experiment. It is shown on the right at the top of your computer screen.

Enjoy!

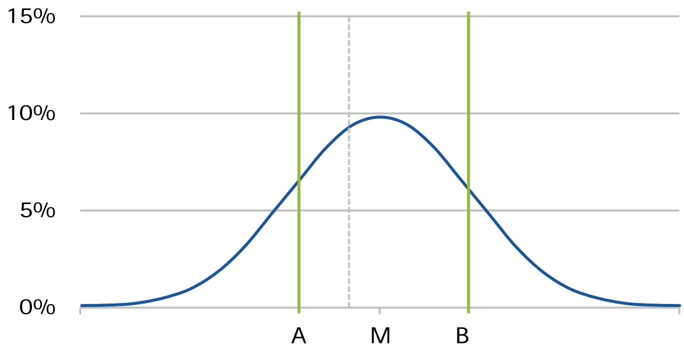
PHASE I

This Phase consists of an investment decision and a questionnaire.

First you will be asked to decide how to invest your initial 1000 experimental tokens choosing among six alternative investments. Each investment is a portfolio that consists of different types of assets. For each of them you will be able to view graphically, the distribution of returns.

In the screenshot at the top you will see a graphical representation of the six available portfolios; clicking on each of them you will be able to enlarge the image. Each graph, as in the figure below, represents how the percentage of return of that investment is distributed; the average return (M) is indicated by the peak of the distribution, while we indicate with two green vertical lines (A and B) the area of the distribution that coincides with 68% (that is, with a 68% probability that the choice of that portfolio will guarantee a return between the lower limit 'A' and the upper limit 'B').

Portfolio representation



The dotted line indicates 0%; therefore, the values to the right of the dotted line indicate positive investment returns. The values to the left of the dotted line represent negative returns, at which the investment result will be lower than the amount initially invested. 0% indicates that the portfolio in which you have invested will yield an exact sum equal to the capital invested (1000 trial tokens).

Example: If your investment guarantees a 68% return between -1% (A) and 4% (B), it means that your end result is distributed, with a 68% probability, between 990 tokens (1,000-1%(1,000)=1,000-10) and 1,040 tokens (1,000+4%(1,000)=1,000+40).

Each portfolio that will be presented to you is characterised by different probability distributions, to signal a different risk for each investment: your task is to choose the portfolio in which you prefer to invest the amount you have available (NB: you must necessarily choose one of them and invest in it the entire initial amount).

Once you have made your choice individually and independently, the computer will present a series of questions to which you will have to answer with great attention and sincerity because on them depends the performance of *Phase II* of the experiment. At the end of the questionnaire, the experimenters will give you instructions for the next phase of the experiment.

PHASE II [TREATMENT R]

At this Phase the computer will formulate the most suitable portfolio for your investor profile, given the answers you provided in the *Phase I* questionnaire.

You will inspect your personalised advice on the computer screen and you will receive a printed-copy of it in a folder with your identification number (i.e. the number on your computer's screen on the top right).

Once you have picked up the folder you can go back to the computer room and sit at your workstation.

In particular, the computer will ask you if you want to review your choice of investment in *Phase I* of the experiment. The same instructions also apply to this decision.

The computer will ask you to decide again in which portfolio to invest your initial 1,000 experimental tokens among the same six alternative investment portfolios presented graphically on your computer screen in *Phase I*.

Once you have made your choice, the computer will randomly calculate the return on your investment, which will be paid out at the end of the experiment.

ATTENTION: your payment for the investment will depend on the final investment choice you make in *Phase II*.

PHASE II [TREATMENT H]

At this Phase, a financial advisor will recommend to you the most suitable portfolio for your investor profile, given the answers you provided in the *Phase I* questionnaire.

You will receive a printed-copy of your personalised advice in a folder with your identification number (i.e. the number on your computer's screen on the top right).

Once you have picked up the folder you can go back to the computer room and sit at your workstation.

In particular, the computer will ask you if you want to review your choice of investment in *Phase I* of the experiment. The same instructions also apply to this decision.

The computer will ask you to decide again in which portfolio to invest your initial 1,000 experimental tokens among the same six alternative investment portfolios presented graphically on your computer screen in *Phase I*.

Once you have made your choice, the computer will randomly calculate the return on your investment, which will be paid out at the end of the experiment.

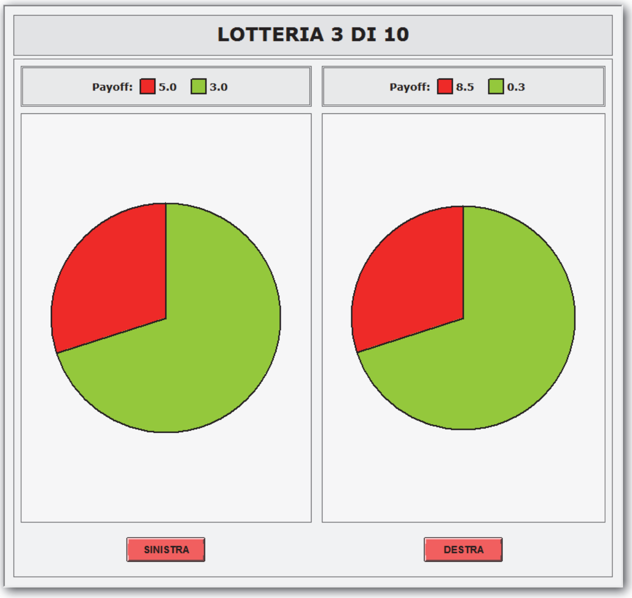
ATTENTION: your payment for the investment will depend on the final investment choice you make in *Phase II*.

PHASE III

In this Phase you will be asked to choose between lotteries involving different prizes and earning possibilities. You will be presented with a series of 10 pairs of lotteries to choose among.

For each pair of lotteries, you will have to indicate which of the two you prefer to play. In fact, you will have the opportunity to play one of the lotteries you have chosen at random and get paid depending on the result you get from it. Think about which lottery you prefer in each choice.

Below is an example of how the computer will present each couple of lotteries to choose among. The screen you will see will be larger and easier to read.



Notes (not part of the original instructions): this figure represents the actual choice from the software used for the experiment. The top figure reports the number of the lottery 'Lottery 3 of 10', and the left button 'Sinistra' means 'Left' and the right button 'Destra' means 'Right'.

Each lottery assigns a given probability to winning four different prizes, respectively: € 0.3, € 3, € 5 and € 8.5 with a different colour that will remain the same for all 10 rounds.

Notes (not part of the original instructions): this figure represents the fortune wheel from the software used for the experiment: the text tells to participants 'The computer will now randomly select one of the ten lottery pairs'.

After everyone has completed this Phase, the computer will randomly determine the round that will actually be played and your gain.

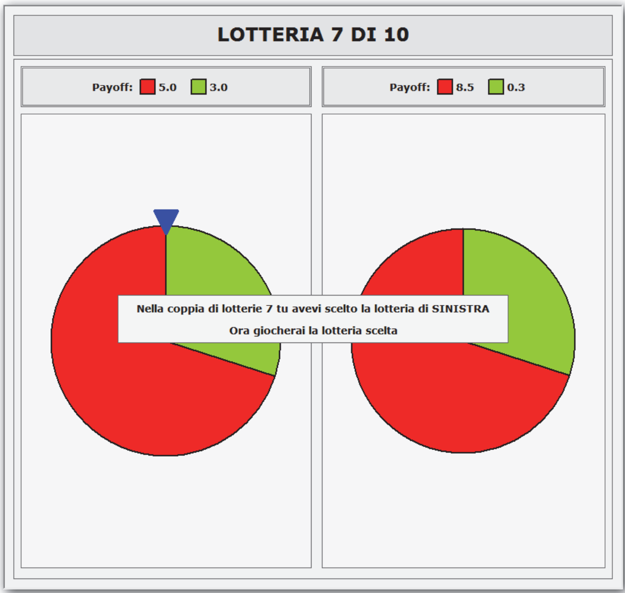
A 'wheel of fortune' will appear on your screen with a hand that will stop at one of the 10 rounds. Each round has the same probability of being drawn. Once the round to play has been drawn, the computer screen will show the two corresponding lotteries and will display the one of the two that each of you had chosen in that round.

For example, suppose you preferred, as exemplified below, the LEFT lottery. A moving hand will appear on it:

- if the hand will stop in the green area, you will be paid €3 for this Phase at the end of the experiment;
- if the hand stops in the red area, you will be paid €5 for this Phase at the end of the experiment.

In summary, your monetary gain for this Phase is determined by three things:

- from which of the 10 rounds will be drawn to be implemented for payment;
- from which lottery you have preferred, RIGHT or LEFT, in that round;
- the result of the draw in your chosen lottery.



Notes (not part of the original instructions): this figure represents the lottery chosen to be actually played: the text tells to participants 'In pair lottery number 7 you have chosen the LEFT lottery. Now you will play it.'

Be careful: this is not a test of skill in choosing the 'best' lottery from those presented in each pair, as none of the lotteries presented is necessarily better than the other. The lottery you choose depends on your personal taste. Other participants may have different tastes, so their choices are not important to you. So work quietly and make your own choices by reflecting carefully on each lottery.

YOUR PAYOFF FROM THE EXPERIMENT

Your total gain from the experiment will be determined by the sum of the gains you will have earned in *Phase II* and *Phase III* of the experiment.

You will be informed of the percentage return on the portfolio chosen in *Phase II* and then on the final amount. To this payoff it must be added the gain from the lottery drawn in *Phase IV*.

In conclusion, the gain of this experiment depends on:

- the return extracted according to the investment distribution chosen for *Phase II*;
- the gain made in the lottery drawn during *Phase III*.

Appendix 2

Stage 1 questionnaires

Socio-demographic questionnaire

Gender

- Male
- Female

Age (open question)

Geographical origin

- North
- South
- Center
- Islands

Level of education (your course for Luiss students)

- High school diploma
- Triennial
- Specialist
- Master/PhD
- Other

Grable and Lytton's Risk Tolerance Quiz (2003)

Students participating in the experiment were asked to fill the translated version of the Grable and Lytton's Risk Tolerance Quiz (2003); some questions referring to monetary values expressed in dollars were adapted and monetary values were expressed in euros.

1. In general, how would your best friend describe you as a risk taker?
   a. A real gambler
   b. Willing to take risks after completing adequate research
   c. Cautious
   d. A real risk avoider

2. You are on a TV game show and can choose one of the following. Which would you take?
   a. $1,000 in cash
   b. A 50% chance at winning $5,000
   c. A 25% chance at winning $10,000
   d. A 5% chance at winning $100,000

3. You have just finished saving for a 'once-in-a-lifetime' vacation. Three weeks before you plan to leave, you lose your job. You would:
    a. Cancel the vacation
    b. Take a much more modest vacation
    c. Go as scheduled, reasoning that you need the time to prepare for a job search
    d. Extend your vacation, because this might be your last chance to go first-class

4. If you unexpectedly received $20,000 to invest, what would you do?
    a. Deposit it in a bank account, money market account, or an insured CD
    b. Invest it in safe high quality bonds or bond mutual funds
    c. Invest it in stocks or stock mutual funds

5. In terms of experience, how comfortable are you investing in stocks or stock mutual funds?
    a. Not at all comfortable
    b. Somewhat comfortable
    c. Very comfortable

6. When you think of the word 'risk' which of the following words comes to mind first?
    a. Loss
    b. Uncertainty
    c. Opportunity
    d. Thrill

7. Some experts are predicting prices of assets such as gold, jewels, collectibles, and real estate (hard assets) to increase in value; bond prices may fall, however, experts tend to agree that government bonds are relatively safe. Most of your investment assets are now in high interest government bonds. What would you do?
    a. Hold the bonds
    b. Sell the bonds, put half the proceeds into money market accounts, and the other half into hard assets
    c. Sell the bonds and put the total proceeds into hard assets
    d. Sell the bonds, put all the money into hard assets, and borrow additional money to buy more

8. Given the best and worst case returns of the four investment choices below, which would you prefer?
    a. $200 gain best case; $0 gain/loss worst case
    b. $800 gain best case; $200 loss worst case
    c. $2,600 gain best case; $800 loss worst case
    d. $4,800 gain best case; $2,400 loss worst case

9. In addition to whatever you own, you have been given $1,000. You are now asked to choose between:
   a. A sure gain of $500
   b. A 50% chance to gain $1,000 and a 50% chance to gain nothing

10. In addition to whatever you own, you have been given $2,000. You are now asked to choose between:
   a. A sure loss of $500
   b. A 50% chance to lose $1,000 and a 50% chance to lose nothing

11. Suppose a relative left you an inheritance of $100,000, stipulating in the will that you invest ALL the money in ONE of the following choices. Which one would you select?
   a. A savings account or money market mutual fund
   b. A mutual fund that owns stocks and bonds
   c. A portfolio of 15 common stocks
   d. Commodities like gold, silver, and oil

12. If you had to invest $20,000, which of the following investment choices would you find most appealing?
   a. 60% in low-risk investments 30% in medium-risk investments 10% in high-risk investments
   b. 30% in low-risk investments 40% in medium-risk investments 30% in high-risk investments
   c. 10% in low-risk investments 40% in medium-risk investments 50% in high-risk investments

13. Your trusted friend and neighbor, an experienced geologist, is putting together a group of investors to fund an exploratory gold mining venture. The venture could pay back 50 to 100 times the investment if successful. If the mine is a bust, the entire investment is worthless. Your friend estimates the chance of success is only 20%. If you had the money, how much would you invest?
   a. Nothing
   b. One month's salary
   c. Three month's salary
   d. Six month's salary

Risk Tolerance Quiz Scoring Grid
The scoring for the risk tolerance quiz questions is as follows:

1.	a=4; b=3; c=2; d=1	8.	a=1; b=2; c=3; d=4
2.	a=1; b=2; c=3; d=4	9.	a=1; b=3
3.	a=1; b=2; c=3; d=4	10.	a=1; b=3
4.	a=1; b=2; c=3	11.	a=1; b=2; c=3; d=4
5.	a=1; b=2; c=3	12.	a=1; b=2; c=3
6.	a=1; b=2; c=3; d=4	13.	a=1; b=2; c=3; d=4
7.	a=1; b=2; c=3; d=4		

Score interpretation:
18 or below = Portafoglio 1 (low risk tolerance)
19 to 22 = Portafoglio 2
23 to 28 = Portafoglio 3
29 to 32 = Portafoglio 4
33 to 39 = Portafoglio 5
40 and above = Portafoglio 6

Other questions

Knowledge and experience

I have made several investments in financial products in recent years

- totally agree
- agreed
- partially agree
- I disagree
- totally disagree

Education level

- High school Diploma
- Degree
- Degree in Economics and Finance
- Other

Compared to my monthly income, my saving capacity is

- 0%
- 0-5%
- 5-10%
- 10-20%
- >20%

I often buy or sell financial products such as mutual funds, stocks or bonds

- totally agree
- agree
- partially agree
- disagree
- totally disagree

How do you consider your-self

- I consider myself an impulsive person, I act quickly riding waves of emotion
- I consider myself a thoughtful person, very careful before making a decision
- I consider myself a methodical person, before making a decision I plan and organize everything with precision and forethought
- When I make a decision I am much influenced by others
- Before making a decision I need the people closest to me to give me support

Imagine that you are alone in a forest and suddenly you hear a noise in the bushes. What do you think?

- It will certainly be a dangerous animal, take a stick to deal with it
- It will certainly be a dangerous animal, run away or ask for help
- It could be an interesting person, I wonder if I'm dressed properly
- It could be an interesting person, we could take a walk together
- It could be a wounded animal to be rescued

During a meeting/job interview your presentation received a lot of criticism. How do you feel?

- I get very angry because they did not understand what I'm worth, so I will try to oppose this energetically
- I'm sorry and will try to produce more material to explain better
- The criticism is an expression of interest, I will try to interest them
- I'm worried, I have to find someone to help me
- I have done something wrong in the presentation, I must try harder

You are in a big city you do not know. You can choose the kind of transport you will use to get around. Which do you choose?

- Taxi
- Bicycle
- Public Transport
- Scooter or motorcycle
- Car

You are travelling and you get hungry. What do you do?

- Look for a traditional cuisine restaurant or a well-known chain of restaurants
- Go into a supermarket and buy the ingredients to make me a sandwich
- Get a recommendation from a local
- Follow the directions of a tour guide
- Go into the first place I find

Tomorrow you have a first date. Who is the person you are going out with?

- A person I have known for many years
- A person presented by trusted friends
- A person you have met travelling
- A person met in a few minutes at a party
- A person met in chat

You have decided to take a trip. What is your ideal type of trip?

- Adventure (e.g. backpacking)
- Not organised, looking for shelter along the way (B&B, etc.).
- Organised by me, or by friends
- In tourist facilities
- Private house
- Organised by others (tour operators, agencies)

You have received a gift (like a smart-box). What would you like it to be?

- Action/Adventure (you can do one of the following activities: parachute, free-climbing, rafting, diving, bungee-jumping, rally, motocross)
- Nature & Sport (you can engage in any of the following activities: windsurfing, horse trekking, hiking, mountain-biking, kayaking on the river, sailing)
- Energy-Fitness (subscription to a sports center with a wide range of activities: gym, spinning, swimming, running, martial arts, dance-fitness)
- Lifestyle (you can attend one of the following activities: cooking, tasting wines and beers, the course of music and singing, mime and theatre course)
- Well-being (the choice is between: beauty farm, relaxation in historic villas, shiatsu massage or Ayurvedic spa treatments, Spa)

Post-experimental questionnaires

Financial literacy test by Lusardi and Mitchell (2014) and by Van Rooij et al. (2011)

Students participating in the experiment were asked to answer the translated version of the following questions; questions referring to monetary values expressed in dollars were adapted and monetary values were expressed in euros.

Suppose you had \$100 in a savings account and the interest rate was 2 percent per year. After 5 years, how much do you think you would have in the account if you left the money to grow:

- more than \$110
- exactly \$110
- less than \$110
- do not know
- refusal

Imagine that the interest rate on your savings account was 1% per year and inflation was 2% per year. After 1 year, how much would you be able to buy with the money in this account?

- More than today
- Exactly the same
- Less than today
- Do not know
- Refusal

Do you think that the following statement is true or false? «*Buying a single company stock usually provides a safer return than a basket of stocks*»

- True
- False
- do not know
- refusal

A 15-year mortgage typically requires higher monthly payments than a 30-year mortgage, but the total interest paid over the life of the loan will be less.

- True
- False
- Don't know
- refusal

If the interest rate falls, what should happen to bond prices?

- Rise
- Fall
- Stay the same
- None of the above
- Do not know
- Refusal

Self-assessed financial literacy

On a scale from 1 to 10, where 1 means any competence and 10 means very high, how would you assess your overall financial knowledge?

How would you assess your overall financial knowledge with respect of other participants in the experiment?

- strongly above the average
- slightly above the average
- on average
- slightly below the average
- strongly below the average

Digital Literacy test by Hargittai (2009)

How familiar are you with the following computer and Internet-related items? Please choose a number between 1 and 5, where 1 represents no understanding and 5 represents full understanding of the item.

The order of the items on the two lists—constant on all surveys—was as follows (with the bogus items in italics).

First list: JPEG, frames, preference settings, newsgroups, PDF, refresh/ reload, advanced search, proxypod, weblog, JFW, bookmark, bookmarklet, spyware, bcc (on e-mail), and blog.

Second list: tagging, tabbed browsing, RSS, wiki, malware, social bookmarking, podcasting, phishing, web feeds, firewall, filtibly, cache, widget, favorites, and torrent.

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