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Psychological Profile and Investment Decisions

Abstract

We conducted a study to test whether psychological factors influence stock trading behaviour in a sample of 176 individuals. Through a trading simulation game, we combined financial data with the scores from demographics, psychological traits and risk-attitudes. As a result, we found that conscientiousness is a significant variable in explaining higher trading volume and greater risk-taking. Demographics and risk-attitude measures moderated the individual investment choices. Financial decision-making and the extent that we trade stocks are not only determined by our attitudes towards risk, but also by the level of our conscientiousness. These results have implications for modelling decisions under risk as well as the provision of financial advice.

Keywords: financial trading; investment style; personality traits; risk attitude;

1. Introduction

Developing theories on how financial market participants should behave is the basis of traditional financial economics. Over the past 30 years, there has been a greater emphasis on how financial market participants actually behave rather than how they should behave. Obtaining a better understanding of how financial market participants behave gives a better understanding of how financial markets operate. This in turn can lead to better policy and models on investment choice. A major hurdle in this research is obtaining data on the decision-making processes of individuals.

The question of what drives a person to make financial decisions depends upon the type of financial decision being made and a raft of other factors. These factors can be broken into two components: external factors and internal factors. External factors include the environment and the social setting the investor faces. Internal factors include the psychological and demographic characteristics of the individual.[1] We concentrate on these internal factors and we consider their impact on stock trading behaviour of a sample of investors in a stock-trading game. Dhar and Zhu (2006) and Grinblatt et al. (2011) are the two studies central to the work on the analyses of the relation between investor personal traits and trading heuristics. Dhar and Zhu (2006) find that the level of investor literacy impacts upon the disposition effect, while Grinblatt et al. (2011) empirically demonstrate how a measure of intelligence (IQ) is a significant driver for heterogeneity in investment behaviour. Both studies imply that the systematic differences in economic phenomena can be described through cross-sectional study, in which personal and cognitive information are matched with financial records.

From Dhar and Zhu (2006) and Grinblat et al. (2011) and inspired by the literature on the effect of psychological variables on risky decision-making (Lauriola & Levin 2001; Nicholson et al. 2005; Mishra & Lalumiere 2010, 2011), we construct a unique individual dataset to explore what psychological traits account for differences in actual financial investment decision-making.

[1] These other factors include noncognitive abilities (see Parise and Peijnenburg, 2019).

Despite a long stream of research that links individual preferences to specific psychological traits, we offer a complete analysis to depict the demographic and psychological investor characteristics able to affect individual financial decisions. In particular, from the work of Durand et al. (2013) and Cecchini et al. (2018) on the relationship between personality traits and the disposition effect, we argue that personality data can be useful to improve existing models in explaining several facts about financial trading that have not received sufficient attention. In this paper, we describe the insights of an experimental study designed to better understand the variance around investment choice, particularly the volume of trading and the percent of wealth invested in risky stocks. Our results demonstrate a link between personality traits and demographic information and individual investment decisions.

Using experimental analysis, our paper focuses and controls at the level of each individual. The sample is composed of 176 students from the Economics and Engineering Faculties at University of Bologna (Italy) who were invited to participate in a trading competition based on Weber and Camerer (1998). Their psychological characteristics were recorded through a series of tests and assessments.

The paper begins with the study of personality trait effects on the volume of trading and the percentage of investment in risky stocks as proxies for trading activity. This result is distant from the traditional theories in which an individual should base their decisions on the maximization of the expected value of the stock return and risk aversion. Indeed, our insight seems to support the effect of personality characteristics in shifting the individual investment behaviour far from what is predicted for a risk-neutral trader. In particular, controlling for trading experience and other demographics information, there is evidence of a relation between the trait of conscientiousness in explaining the percentage of funds invested in risky stocks and the amount of trading activity.

Among the sample, we show that females exhibit less market activity than males, supporting the previous literature on gender differences in risk-taking (Byrnes et al. 1999; Fellner & Maciejovsky 2002).

Finally, from the relation between risk attitude and trading volume, we investigate whether a psychometric measure of risk preferences (DOSPERT, financial and gambling domain) relates with the individual behaviour. While we demonstrate that DOSPERT correlates with participant trading behaviour (this has been already established extensively in the literature back as far as Barber and Odean (2001), we do not find a convergence in the effect of personality traits over the two measures.

These results offer several theoretical, empirical and practical contributions. First, a missing explanation of the mechanisms that underlie the role of individual characteristics in driving different performances is revealed. Focusing on *how* and *which* personality traits influence single facets of individual behaviour, our study aims at providing a better understanding of *where* these decisions come from. Second, in proposing a study at the individual level, our insights may help motivate theorists to consider the heterogeneity in personality traits in normative models that capture anomalies in asset pricing and portfolio choices such as insufficient or naive diversification (French & Poterba 1991), excessive trading (Odean 1999) and underreaction (overreaction) to information (Frazzini 2006).

Third, our study can call to the attention of investment firms and financial companies in guiding their recruiting and training practices, as well as that of regulators in educating individuals in helping them make better investment decisions.

The paper is organised as follows: Section 2 provides a brief literature review on personality traits and risky decision-making; Section 3 presents the theory behind the goals of the paper; Section 4 documents the design of the experiment while the results are described in Section 5. The final discussion is provided in Section 6.

2. Literature Review

Personality traits

The question of what drives an individual to make an investment decision under risk has been widely investigated over many decades (Lo et al. 2005; Dhar & Zhu 2006). From the cognitive literature on psychological traits, there is substantial evidence of a link between personality traits and heterogeneity in individual decision-making (Fenton-O'Creevey et al. 2004; Grinblatt & Keloharju 2009; Grinblat et al. 2011; Durand et al. 2013; Conlin et al. 2015, Cecchini et al. 2018). Through emotions and cognitions, we elaborate a series of conscious and unconscious processes that result in our final decision. Psychologists categorize these patterns in human personality traits.

A full literature review on personality traits is not the aim of this work. However, in this section, we highlight some salient points from the literature that could help the reader through the paper. Starting from its definition, a personality trait is a stable set of thoughts, actions and emotions that influence the behaviour of an individual during their life (Kassin 2003).

A long stream of theories succeeded over the years defining personality traits as stable over time, different across participants and able to influence people's behaviour. Measurement scales were developed to provide a better picture of the traits. Tupes and Christal's (1961) five-factor model of personality traits defines neuroticism, extraversion, conscientiousness, openness to experience and agreeableness as being the key psychological characteristics of individuals. These have become known as the Big-Five personality traits. The first trait, extraversion, is often related with dimensions as being outgoing, energetic, sociable, friendly, talkative and gregarious. Neuroticism or emotion stability is associated with anxiety, shyness, irritability and moodiness. Common dimensions linked with the trait of conscientiousness include being efficient, organised, prepared, dependable, self-disciplined and careful. Openness to experience has dimensions including intellectual ability, curiosity, high imagination, inventiveness and unconventional idea formation. Finally, those who score high on agreeableness generally are more courteous, modest, undemanding, warm, altruistic, trusting and generous. The heterogeneity of the resulting psychological constructs beyond each of the five traits is the main criticism directed at the Big-Five model (Boyle 2008). The fact that the underlying psychological processes of each trait are not always orthogonal raises concerns about the Big Five's construct validity (Saucier 2002). However, the Big-Five model appears to show consistency in describing normal personality trait sphere, and its structure seems to find reliability across ages and cultures (Schacter et. al 2011). The accuracy of the Big-Five traits is widely accepted in psychological literature, and the assessment of each trait takes place mainly through self-reported questionnaires.

Several studies established substantial evidence in using these personality measurements to explain heterogeneity across population. From caffeine consumption to learning processes, social psychologists employed questionnaires to analyse an endless list of behaviours, often combining various research fields (Ozer & Benet-Martinez 2006). Since their role in the understanding of individual differences in participants' cognitive, emotional and motivational processes, the Big-Five traits is one way of detecting the differences across participants in decision-making.

Personality traits and risky decision-making

Several researchers have focused on the role of the personality traits in addressing an endless list of behaviours. For our purpose, we restrict the area to those that have direct implications with financial markets and financial decision-making. For example, in the study of the investment decisions, psychologists and economists have shown that the differences in the preferences expressed by the investors involve specific risk-attitude heterogeneity (Lauriola & Levin 2001; Nicholson et al. 2005; Lo et al. 2005; Mishra & Lalumiere 2011). Consequently, various models have been developed to examine the relationship between Big-Five personality traits and risk-taking in financial decision-making.

In testing this correlation, Nicholson et al. (2005) observe that sensation seeking (a dimension often associated with the attitude toward varied and novel experiences and feelings) is highly related with risky financial decision-making.[2] These findings are supported by several studies on gambling preferences (Wolfgang 1988; Wong & Carducci 1991; Lauriola & Levin 2001; Mishra & Lalumiere 2010, 2011; Gambetti and Giusberti, 2012; Akhtar and Das, 2019), which reveal that higher-risk attitude is positively associated with extraversion and openness to experience (the traits often associated with sensation seeking) while agreeableness and conscientiousness exhibit relationships with lower risk aversion.[3] Mayfield et al. (2008) extend this work to consider the impact of risk aversion and personality traits on short and long-term financial decisions. In a sample of undergraduate students they find that different personality traits impact short and long-term financial intentions. Neuroticism was negatively related to short-term investing while extraversion was positively related to short-term investing. Mayfield et al. (2008) also consider the impact of attitudes to risk and possible decision making. Here, they find risk aversion is only a significant predictor of short-term financial intentions. However, the main flaw in these studies is that decisions

[2] The same finding has been recorded in the empirical work by Grinblatt and Keloharju (2009) in which sensation seeking is related to the tendency of investors to be active on the stock-market.
[3] See Roberti (2004).

regarding actual financial choices are not considered; only attitudes and intentions are considered.

To better understand how personality traits affect risky decision-making, a common strategy postulate a binary role of the traits for negative and positive states. Especially, according to Lauriola and Levin (2001), the score of some traits is identified in specific preferences whenever a participant is faced with gain and loss trials. For example, in a lottery task where a sure gain is the alternative of an uncertain higher gain, highly neurotic people will manifest a risk-averse behaviour choosing the first option. Conversely, in the loss domain, the same people will display a preference for the risky option that might lead to the decision that entirely avoids the loss (risk-seeking over losses).

The influence of personality in the sensitivity to punishment and reward cues is the basis of the model developed by Gray (1987). Gray proposes that two stimulus systems underlie human behaviour: a behavioural activation system (BAS) that regulates the motivations in obtaining appetite goals; and a behavioural inhibition system (BIS) where aversive motives are controlled to avoid something unpleasant. Through a 20 items questionnaire, Gray (1987) identifies some differences in the BIS/BAS systems across the population, and he correlates this variability differences in personality traits. In particular, Gray finds that where the approach to avoid punishment signals the biological foundation of anxiety, the dimension of impulsivity seems to play a relevant role in the regulation of behaviours towards rewards. Faff, Mulino and Chai (2008) provide a link between financial risk tolerance and risk aversion using online lottery choice experiments. They contrast real and hypothetical payoffs, low and high stakes, decisions involving gains and losses and order effects. They find that financial risk tolerance and risk aversion are strongly aligned.

The fact that some personality traits predict risk-taking preferences during decision-making has been also confirmed by several meta-analytic studies over the last 30 years (Barrick & Mount 1991; Tett et al. 1991; Hurtz & Donovan 2000). For example, Barrick and Mount (1991) demonstrate this relation using the personality model in a performance evaluation system among groups of professionals, policemen, managers, sales and skilled/semi-skilled participants. While Barrick and Mount (1991) focus mainly on job-performances (high conscientiousness/low impulsivity validates greater performances for all occupations), Fenton O'Creevy (2004), in a sample of 118 investment bankers, shows that higher emotional stability combined with higher openness to experience are the main ingredients for a successful financial trader.

The significant correlation between openness to experience and positive trading performances has motivated some researchers to investigate in detail if there are some dimensions that better explain this relation. To this end, several authors analyse the effect of intelligence on trading behaviour (Chevalier & Ellison 1999; Gottesman & Morey 2006).[4] Grinblatt et al. (2011) combine IQ measures and trade data for a sample of investors in the Finnish market, and they document that the raw scores of IQ is a significant predictor of high returns and less biased trading behaviour. In particular, during their study, the authors highlight how high-IQ investors are not affected by behavioural biases, such as the disposition effect, but on more rational factors such as transaction costs. Using a similar Finnish dataset, Conlin et al. (2015) measure the impact of personality data on individual stock-market participation.[5] The authors show a role of the subscales of extraversion (excitability, extravagance and exploration) in increasing the number of debt and assets held by investors. Moreover, while providing empirical evidence about a positive association between information acquisition and trading frequency, Tauni et al. (2015) analyse whether the investor personality could act as a moderator in the relation among information acquisition and market activity. Tauni et al. (2015) demonstrate that extraversion and conscientiousness positively moderate the relationship between information acquisition and trading frequency; and openness negatively moderates the relationship between information acquisition and trading frequency.

Finally, Durand et al. (2013) and Cecchini et al. (2018) investigate the relation between the personality traits and the disposition effect. They document that extroverts quickly sell the stock at a gain in order to receive a burst of utility while conscientious participants suppress impulsivity waiting for higher cumulative returns. Cecchini et al. (2018) demonstrate the importance of 'openness to experience' to better value information to achieve higher

[4] Intelligence has been depicted as one of the main elements of openness to experience (Ashton et al., 2000; Harris, 2004).

[5] The authors use personality data from a battery of Temperament and Character Inventory (TCI) questionnaires. The TCI model differs but correlates with the more common Big-Five traits (Costa & McCrae; 1992). For more information about TCI see Cloninger et al. (1993).

outcomes, and a tendency for conscientious participants to suppress impulsivity, patiently waiting for higher cumulative returns.

Unfortunately, there is little research that clearly investigates the overall influence of the Big-Five personality traits on individual trading behaviour and risky investment decisions. In the next section, with the aim of reducing this gap, we analyse the role of psychological traits in explaining the financial behaviour across individuals.

3. Theoretical framework and hypotheses development

The motivation underlying this study can be traced back to research on broader behavioural aspects associated with personality traits. For example, as from Digman and Takemoto-Chock (1981), McHenry et al. (1990) and Barrick and Mount (1991), conscientiousness usually predicts superior job performances for different occupations. Individuals who exhibit high conscientiousness manifest respect for duties, perseverance and the ability to organise themselves efficiently. This capacity allows for better performance. Within the self-discipline construct, the trait of conscientiousness underlies an attitude to suppress impulsivity that leads to lower risk-seeking behaviours (Gray 1987). In a trading perspective, we hypothesise that the boundaries of conscientiousness drive careful and more precise investment decision-making, which is evident in relatively lower volumes of trading. In relation to risk behaviour Nicholson et al. (2005) document that conscientiousness should also negatively correlate with risk taking. This leads to our first hypothesis:

Hypothesis 1. *Conscientiousness is negatively related to the magnitude of individual trading volume and risk taking.*

With opposite outcomes to conscientiousness, Carrigan (1960) shows a relation between impulsivity and extraversion. Individuals with higher levels of extroversion are characterised by an attitude toward unplanned rapid responses with relatively less concern for future outcomes. Extroverts are relatively more sensitive to rewards and, from Costa and McCrae (1992), there is evidence of their preference for immediate certain gains rather than uncertain higher delayed ones (Cecchini et al. 2018). Furthermore, the greater the value obtained after a positive induced-affect, the higher the probability that these investors repeat the same behaviour to receive similar burst of utility (DeYoung 2014). This implies a recurring dependent behaviour. Therefore, individuals with relatively higher levels of extraversion are more likely to have higher volumes of trading. Nicholson et al. (2005) finds that extraversion correlates with risk seeking behaviour. This leads to our second hypothesis:

Hypothesis 2. *Extraversion is positively related to the magnitude of individual trading volume and risk taking.*

In participants with low emotion stability, anxiety generally increases the chance to overestimate the expectations of bad results during negative states (Eysenck & Eysenck 1985). Butler and Mathews (1987) and Stober (1997) reinforce this theory by suggesting a role of neuroticism (the opposite of emotion stability) on risk-averse behaviour, while the BIS/BAS model considers the aim of avoiding a punishment signals as the biological underpinning of the sub-dimension of anxiety. We hypothesise that when a stock experiences a price decrease, investors with higher levels of neuroticism ascribe more value to that price decrease which activates a relatively stronger response to this decrease. Rather than realising the loss, they maintain their position in the market as they now prefer the uncertain future outcome that could reduce the actual negative balance through a price increase. Over time, this results in relatively lower trading behaviour and lower risk taking (Nicholson et al., 2005). According to this reasoning, this leads to our third hypothesis:

Hypothesis 3. *Neuroticism is negatively related to the magnitude of trading volume and risk taking.*

The personality trait of agreeableness does not clearly associate with individual trading behaviour. This trait refers to the attitude to interact with other people in a friendly way and to maintain good networks with them. Although this trait can be used to forecast performances of specific tasks in which social-dimensions are important (e.g., sales and management tasks), it is difficult to identify individual investment behaviour associated with agreeableness (Barrick & Mount 1991). In the financial domain Nicholson et al. (2005) finds that agreeableness is negatively related to risk seeking behaviour. This leads to our fourth hypotheses:

Hypothesis 4a: *There is no relation between agreeableness and the magnitude of the trading volume.*

Hypothesis 4b: *There is a negative relation between agreeableness and risk taking.*

Finally, we analyse the trait of openness to experience on trading behaviour. As mentioned before, this trait underlies the dimensions of intellect, curiosity, imagination and unusual ideas. Following Grey's model (1987), a person who scores high in openness to experience has the opposite behaviour from what is observed for neuroticism. The trait of openness to experience negatively correlates with the behavioural inhibition system that regulate the overreaction to negative signals (Smith & Boeck 2006). Individuals with high levels of openness assimilate all the information available and act on such information relatively more readily. Negative outcomes are loaded with relatively lower weights. This suggests that individuals with relatively higher levels of openness are likely to trade more frequently and be greater risk takers (Nicholson et al., 2005). This leads to our fifth hypothesis:

Hypothesis 5. *Openness to experience is positively related to the magnitude of the trading volume and risk taking.*

In this paper, we test the role of the Big-Five personality traits in explaining individual investment choices and in particular their trading behaviour and their investment in risky assets.

4. Methodology – Experimental Protocol

We recruited 176 participants who voluntarily agreed to participate in an investment trading simulation game. Participants were graduate and undergraduate students from Engineering and Economics Faculties at the University of Bologna (Italy). The recruitment process consisted of several announcements introducing the trading game during classes and inviting participation. Staff of the Department of Management at the University of Bologna (DiSA) organised the game. In the announcements, participants were advised about the game details and the associated rewards. A total of 176 participants agreed to participate in 8 different sessions at the informatics laboratory of the University of Bologna. On average, participants took 45 minutes to complete all the tasks associated with the game.[6]

[6] The study was approved by the ethics committee of the University of Bologna. Approval no: Prot. 68087 and reviewed by the ethics committee of the University of Queensland. Clearance no: 2018001636.

The participants provided demographic and general information regarding their knowledge and experience associated with buying and selling stocks and investing. We used a shorter version (50-items) of Goldberg's (1999) public-domain personality survey (IPIP NEO: International Personality Item Pool), and an eight item DOSPERT risk-taking scale for the specific financial/gambling domain (Weber et al. 2002) to identify personality traits and risk preferences respectively. [7]

After the participants provided the demographic and general information and completed the questionnaires, they started the trading simulation game. The trading simulation software was developed to replicate Weber & Camerer (1998). In particular, there are six risky stocks (labelled from A to F) that participants can trade for a total of 14 periods. The participants had an initial budget of 2,000 euro (in experimental currency) to invest during the simulation across any of five risky stocks and the risk-free asset, cash. No short selling was allowed. Money held in cash attracted no interest. The prices of the stocks were randomly generated and could not be affected by buying and selling operations. From Weber and Camerer (1998), we used five different risk classes based on the probability of a change in the price of the stock. The probabilities of a change in price were 65% for one stock, 55% for another stock, 50% for two stocks, 45% for one stock and 35% for one stock. Participants knew the chances of price movements of all six stocks, but they did not know which ones had the specific probabilities of rising (or falling). Finally, after the price increase or decrease was determined for each stock, the price could rise or fall by 1, 3 or 5 euro. All three possibilities were equally likely and independent. This resulted in the expected value of a price change for a randomly chosen stock to be zero.

To help make participants more familiar with the pricing dynamics, the software automatically generated the first 4 periods of prices before any trading occurred. Figure 1 illustrates an example of a stock price time series from the main screen of the simulation model. When the participants made a choice to buy or sell a stock, they knew the historical the last price variation for all of the stocks. In each period, the participants had 2 minutes to analyse the information about the historical prices of stocks and to decide their action and

[7] The sub-scale of DOSPERT that we use in this paper covers the financial domain. In particular, the questionnaire is composed of 8 items: 4 investment items and 4 gambling items in which the subjects rate the likelihood to engage in a risky-behaviour using a 5 point scale (1 = very unlikely to 5 = very likely). The higher is the score, the more risk-seeking the subject.

enter the decision. After these 2 minutes, the software automatically moved to the next period. This trading process continued for 14 sessions.

Insert Figure 1 about here

The simulation granted a financial reward. Specifically, the first classified received a total prize of €165. The second was entitled of €100, the third of €50 and the fourth of €15. The structure of the rewarding system is different from that used in Weber and Camerer (1998) in which at the end of the trading simulation the total experimental value of cash and asset holdings is converted to real currency using a specific exchange rate. In our design, a legitimate concern is about the chance that at the end of the simulation subjects who are experiencing low performances will change their trading behaviour. Especially, these participants might be encouraged to take extreme high risk as a final chance to increase the returns and to win a prize without losing anything. We test this potential bias comparing the investment behaviour between subjects with low and high performances. In particular, we analyse whether these two subsamples differ in the trading activities performed at the ending of the simulation (last three periods) with respect to the investment style followed during all the simulation session. For the value of assets held by the participants, we didn't find any statistical significant difference among the subsamples. Moreover, no evidence of a variation in the total number of assets traded is shown. Indeed, the entire sample exhibits a general trend in reducing the number of securities bought at the end of the simulation. Results in the Appendix.

5. Results

Table 1 provides a summary statistic for the entire sample. In particular, Panel A and B show the demographics and scores for psychological traits of the participants.

Insert Table 1 about here

Among the 176 participants, the mean age is just over 22 years with a range from 19 to 27. Sixty-one percent (69) are undergraduates and 41% (107) are graduates. Of the total sample, 31% (55) are females and 69% (121) are males. In relation to questions regarding stock market knowledge and trading experience in financial markets, 43% (77) indicated stock market knowledge and 8% (15) indicated having trading experience.

Panel B reveals the personality trait data for the Big-Five personality traits of IPIP NEO five-factor model and for the DOSPERT risk-attitude questionnaire. In relation to the personality traits, the scores can range from 10 to 50. The higher the score, the greater that particular trait is present. For example, a higher score for extraversion means the participant is more outgoing, energetic, sociable, friendly, talkative and gregarious. A higher score for emotion stability means the participant is more anxious, shy, irritable and moody. A higher score for conscientiousness means the participant is efficient, organised, prepared, dependable, self-disciplined and less careless. A higher score for openness to experience means the participant is intellectual or curious, possesses higher imagination, inventiveness and is unconventional and a higher score on agreeableness generally indicates the participant is more courteous, modest, undemanding, warm, altruistic, trusting and generous.

While males and females differ on emotion stability (men score higher than women, $p<0.01$), no gender differences are found in four personality traits. Gender differences are found in participants' risk-taking. In line with the previous literature, females are more risk averse than males.[8]

Finally, Panel C describes the individual financial records obtained through the trading simulation. In order to understand the variation in the market activity among the sample, we report the number of stocks exchanged during the trading session and the amount of investment in risky stocks. From Panel C of Table 1, a specific trading behaviour emerges. On average, approximately 90 stocks were bought and sold with approximately 50 stocks bought and 38 stocks sold, and participants invested approximately 70% of their available funds in risky stocks.

5.1 Exploring the Trading Strategy

The main goal of this study is to analyse the participants' trading behaviour and to understand what personality traits and risk attitudes impact risky financial decision-

[8] For detail see the meta-analysis conducted by Byrnes et al. (1999).

making. To gain a better understanding of the relations between these variables, Table 2 contains the correlation coefficients between the variables.

Insert Table 2 about here

From Table 2, the correlations are quite low, except of course on the trading variables. Other notable observations are that conscientiousness and agreeableness negatively correlates with the percentage invested in risky stocks, and that emotion stability positively correlates with all three trading variables. Age positively relates with agreeableness, while gender positively correlates with emotion stability. The DOSPERT measure shows evidence of a different risk-attitude between males and females. In particular, DOSPERT positively relates with gender, which supports previous research of males being more risk seeking than females (Barber & Odean 2001; Agnew et al. 2003; Grinblatt & Keloharju 2009).

Generally, the riskier the participant, the greater percentage invested in risky stocks. Furthermore, gender (male) is significantly correlated with all aspects of trading. Males generally invest a greater percent of investable funds in risky stocks, invest in a greater number of stocks and buy and sell a greater number of stocks than females.

These correlations indicate there may be different effects between personality traits, risk attitudes and financial decision-making. From Table 2, the traits of extraversion and openness correlate with risk attitude, but there is no correlation between these two traits and the percentage invested in risky stocks. Conscientiousness only correlates with risk attitude at the 10% level while emotion stability and agreeableness have no correlation to risk attitude but correlate with the amount invested in risky stocks at the 5% level. Table 2 leads us to negatively answer our question on the convergence of the role of personality traits on real versus hypothetical financial decisions. In particular, there is clear evidence of different activations among the personality dimensions for the market activity and for the DOSPERT risk measure. Indeed, these results suggest that a different mechanism is at play between personality traits, attitudes to risk and real financial decisions.

To gain a better visual understanding of these relationships, we plot the cumulating number of stocks traded by the ranges of each personality traits score. This is shown in Figure 2.

Insert Figure 2 about here

As we move towards higher extraversion and emotion stability, the number of stocks traded rises dramatically. By contrast, for higher scores of conscientiousness, the number of stocks traded significantly reduces. We repeat the same analysis for the amount invested in risky stocks and find a similar consistency with that shown in Figure 2.

5.2 Regression Analysis

As stated in the previous paragraphs, a different mechanism seems to be at play between personality traits, attitudes to risk and real financial decisions. In Model 1, we specify a regression model to better understand the interplay of these variables:

$$NS/\%invested_i = \alpha_i + \beta PT_i + \gamma D_i + \varepsilon_i \quad (1)$$

Where $NS/\%percent\ invested_i$ is the number of stocks traded for each participant i during the period; or the percentage invested in risky stocks for each participant i, PT_i is a matrix of the Big-Five personality traits and D_i are the matrix of demographics including the DOSPERT risk-attitude score for each participant i. Table 3 shows the results of trading volume regressions. In column 1 of Table 3, the dependent variable is the total number of stocks traded during the simulation. In column 2 and 3, we regress the number of stocks bought and sold respectively and in column 4, we regress the percentage of funds invested in risky stocks.[9]

Insert Table 3 about here

At first glance, all regressions are statistically significant with adjusted R^2 of approximately 17%. Across all four models, we find conscientiousness a significant negative predictor of trading and the amount invested in risky stocks. In other words, the more conscientious the participant, the less trading is undertaken and the less invested in risky stocks. This is after

[9] To account for potential outliers in the data we report regression results using robust regression methods. The method used is the robust option in Stata which implements robust standard errors (Huber-White sandwich).

controlling for attitudes to risk. We also find generally a positive relation between attitude to risk and trading as expected. That is, the higher the attitude to risk the greater the trading. Gender is also significant and positive.

In summary, our main results are as follows. We demonstrate that, at an individual level of analysis, there is broad variation in the size of capital invested and number of stocks traded across investors with different psychological traits and demographic characteristics. We find consistency between risky decisions made on the questionnaire with those made during the trading simulation but not for the role of personality traits on the two measures. According to previous psychological literature, gender affects the trading strategy (males have higher trading volume than females) which we also find. We find conscientiousness is a significant variable in explaining variation in a range of proxies associated with trading in stocks. This adds important information in relation to determining levels of risk that individuals might prefer to have in their investments. In particular, it is not only the age, gender and attitudes to risk of individuals but the level of their conscientiousness that determines the amount of risk they prefer.

5.3 Robustness tests

To provide robustness to our results, we first estimate a robust regression using only the DOSPERT risk score and the dependent variables. In all cases, the attitude to risk is positively related to all dependent variables. We then introduce each of the five personality variables into the regressions. In all cases, conscientiousness is the only variable that enters any model with a significant coefficient further supporting the base results. Furthermore, age and gender also maintain significance across all the models. These results are available on request.

6. Discussions and conclusions

Using psychological and financial data obtained through an experimental analysis, we test the role of personality traits in altering investor's trading strategy. We support the cognitive predictions that see a connection between personality traits and individual investment choices. We find that conscientiousness predicts lower trading volume and the percentage invested in risky stocks respectively. This suggests that decisions about investment in risky assets is not only driven by attitudes to risk. Consistent with the existing literature, demographics influence the scoring of personality and of the financial choices (Barber & Odean 2001; Agnew et al. 2003; Grinblatt & Keloharju 2009). In particular, females are less emotionally stable and risk-taking than males. We record differences in trading volume for men and women where males have been found to invest higher portions of their budget in a greater number of stocks than females.

Age relates with personality traits. Younger participants score low on conscientiousness and agreeableness, but age is not good predictor for risk-taking and trading volume.[10]

We interpret the role of conscientiousness in driving higher/lower trading volume as follows. Conscientiousness predicts careful decision-making based on low impulsivity. Faced with investment choices, these participants exhibit a tendency to contain risk-seeking behaviours in favour of focused strategies that involved small amounts of capital invested and, in turn, small number of stocks traded.

Finally, since the participants risk preferences are the key to understanding our results, we investigate whether a psychometric measure of risk attitude (DOSPERT questionnaire) relates with individual behaviours on experimental asset markets and, to what extent, the role of personality traits differs in explaining investment decisions made on paper with those involving real transactions. While we demonstrate that DOSPERT significantly correlates with the participant trading behaviour, we do not find a convergence in the effect of personality traits over the two measures.

This study helps us better understand the heterogeneity in the investment behaviour among individuals. Our findings tie well with the current research that uncovers individual characteristics able to explain variations in human decision-making under uncertainty (Dhar & Zhu 2006; Grinblatt & Keloharju 2009; Grinblatt et al. 2011; Cecchini et al. 2018). In particular, suggesting an effect of some personality traits on the investment choices among participants, we motivate theorists to accommodate individual psychological characteristics in financial models devoted to analysing the market liquidity and the securities price changes. Moreover, the fact that, in our sample, personality traits can explain differences in

[10] Note however there was not a big difference in the age of participants.

trading volume can provide relevant insights for portfolio theory, especially during financial bubbles and crashes.

In line with Grinblatt and Keloharju (2009), to better research these goals and to overcome the limitations of a controlled experimental task (relatively small sample size and self-reported personality questionnaire), we emphasise the importance of a study where real financial data is matched with a proxy of a specific personality traits[11]. Again, to shed light on the underlying mechanism at the base of the relation between personality and investment behaviour further studies are suggested. Financial decision-making and the extent that we trade stocks is not only determined by our attitudes towards risk but also by the level of our conscientiousness. The quest to better understand the mechanisms driving the investment decisions is compelling for both theoretical and practical reasons. By substantiating new models with related neuroscience evidence it is possible to disentangle, taking into account the personality, the individual decision processes by analyzing directly the moment when relative wealth changes (Massaro, 2017). This may clarify which behavioral mechanisms better predict the investor financial decisions and how emotions and traits could regulate these processes (Healey et all). These results have implications for modelling decisions under risk as well as the provision of financial advice. Ongoing research shall test our prepositions combining behavioral and neuroscience methods

[11] Jones et al. (2005); Gurpeguia et al. (2007); Penolazzi et al. (2012).

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Tables and Figures

Table 1: *Summary statistics. Panel A describes demographics variables for the entire sample. Age is the age of the experiment participant. Gender is a dummy variable taking values of 0 if male and 1 if female. Graduate is a dummy variable taking the values of 0 if the participant is an undergraduate student and 1 if she is a graduate student. Stock market knowledge is a dummy variable taking value of 0 whether participant has not knowledge on financial markets and 1 if she has a background education in finance or if she works/worked for stock-market services. Finally, trading experience takes the following values: 0 if the participant has low or no trading experience and 1 if she invested at least for one year. Panel B reports psychological variables for the entire sample. Extraversion, Conscientiousness, Emotion stability, Agreeableness and Openness are the Big-Five personality traits while DOSPERT is a measure of risk-seeking attitude. In conclusion, Panel C describes the main variables to analyse the trading volume in the entire sample. Percentage invested in risky stocks is the percent of total available funds invested in risky stocks by participants during the simulation. Number of stocks is the total number of stocks traded by the participant during the simulation, while number of stocks – bought (sold) refer to the number of stocks bought (sold) by the participant during the simulation*

	Obs	**Mean**	**Median**	**Std. Deviation**	**Minimum**	**Maximum**
			Panel A			
Age	178	22.54	23.00	1.84	19.00	27.00
Graduate	178	0.61	1.00	0.49	0.00	1.00
Gender	178	0.69	1.00	0.46	0.00	1.00
Stock-Market Knowledge	178	0.43	0.00	0.50	0.00	1.00
Trading Experience	178	0.08	0.00	0.28	0.00	1.00
			Panel B			
Extraversion	178	34.92	35.00	4.96	19.20	47.50
Conscientiousness	178	38.46	39.18	5.74	20.00	50.00
Emotion Stability	178	30.94	30.80	7.18	13.30	48.30
Agreeableness	178	34.56	35.00	5.41	17.50	48.20
Openness	178	38.35	38.33	5.07	26.66	49.20
DOSPERT	178	19.56	19.00	4.64	8.00	37.00
			Panel C			
Number of stocks traded	169	90.89	70.00	62.51	12.00	416.00
Number of stocks –bought	169	52.26	43.00	31.52	6.00	193.00
Number of stocks –sold	169	38.63	28.00	31.76	2.00	214.00
% Invested in risky stock	175	70.06	73.04	0.22	0.00	100.00

Table 2: *Correlation matrix between measures of trading volume, personality traits, risk-attitude scale and demographics. E is extraversion, C is Conscientiousness, ES is Emotion stability, A is Agreeableness and O is Openness.*

Variables	**Number of stocks traded**	**Number of stocks bought**	**Number of stocks sold**	**% invested in risky stocks**	**E**	**C**	**ES**	**A**	**O**	**DOSPERT**	**Age**	**Gender**	**Graduate**	**Stock-Market knowledge**
Number of stocks bought	**0.98*** **													
Number of stocks sold	**0.98*** **	**0.95*** **												
% invested in risky stocks	**0.30*** **	**0.37*** **	**0.22*** **											
E	**0.13***	0.13	**0.13***	-0.07										
C	-0.11	-0.12	-0.09	**-0.21*** **	**0.20*** **									
ES	**0.17** **	**0.17** **	**0.15** **	0.09	0.03	**0.16** **								
A	0.02	0.00	0.03	**-0.15** **	0.00	**0.34*** **	**0.29*** **							
O	0.06	0.05	0.07	0.00	**0.29*** **	**0.29*** **	0.11	0.10						
DOSPERT	**0.21*** **	**0.20*** **	**0.22*** **	**0.15** **	**0.23*** **	**0.14***	-0.03	0.07	**0.26*** **					
Age	0.08	0.08	0.08	0.01	**0.02*** **	0.19	0.09	**0.21*** **	0.01	0.03				
Gender	**0.31*** **	**0.31*** **	**0.32*** **	**0.26*** **	0.11	-0.09	**0.32*** **	-0.03	0.06	**0.31*** **	-0.05			
Graduate	-0.07	-0.07	-0.07	-0.05	-0.00	**0.27*** **	0.11	**0.16** **	0.02	-0.11	**0.74*** **	**-0.18** **		
Stock market knowledge	-0.05	-0.05	-0.04	0.11	-0.09	-0.08	**-0.15** **	**-0.19** **	-0.04	0.04	**-.20*** **	-0.02	**-0.16** **	
Trading Experience	0.00	-0.00	0.00	0.03	**0.14***	0.01	-0.05	-0.03	**0.22*** **	0.08	-0.00	0.11	0.00	**0.14***

$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

Table 3 *Regression table: Trading volume. A set of OLS regressions in explaining the differences in the amount of securities traded during the simulation is presented as well as percentage invested in risky stocks. The dependent variables are the number of stocks traded (column 1), the number of stocks bought (column 2), the number of stocks sold (column 3) and the percentage invested in risky stocks (column 4). The independent variables include the personality traits (extraversion, conscientiousness, emotion stability, agreeableness and openness), demographics data (age, gender, education, stock market knowledge and trading experience) and a measure of risk attitude (DOSPERT). Age is the age of the experiment's participant. Gender is a dummy variable taking values of 0 if male and 1 if female. Graduate is a dummy variable taking the values of 0 if the participant is an undergraduate student and 1 if she is a graduate student. Stock market knowledge is a dummy variable taking value of 0 whether participant has not knowledge on financial markets and 1 if she has a background education in finance or if she works/worked for stock-market services. Finally, trading experience takes the following values: 0 if the participant has low or no trading experience and 1 if she invested at least for one year.*

	(1) Number of stocks traded	(2) Number of stocks bought	(3) Number of stocks sold	(4) % invested in risky stocks
Extraversion	6.78	3.61	3.171	-.022
	(1.18)	(1.35)	(1.09)	(-1.25)
Conscientiousness	**-9.21***	**-4.87****	**-4.328***	**-0.039****
	(-1.95)	**(-2.02)**	**(-1.82)**	**(-2.39)**
Emotion Stability	7.61	4.352	3.259	0.023
	(1.46)	(1.59)	(1.28)	(1.17)
Agreeableness	0.23	-0.39	0.631	-0.026
	(0.06)	(-0.21)	(0.34)	(-1.53)
Openness	1.42	0.36	1.062	0.014
	(0.23)	(0.12)	(0.32)	(0.61)
DOSPERT	**1.844***	0.902	**0.941***	**0.006***
	(1.71)	(1.65)	**(1.72)**	**(1.89)**
Age	**7.879***	**4.03****	**3.846***	0.012
	(1.89)	**(2.11)**	**(1.84)**	(0.96)
Gender	**24.91****	**12.32****	**12.59****	**0.085****
	(2.04)	**(1.98)**	**(2.05)**	**(2.03)**
Graduate	-22.43	-11.12	-11.31	-0.005
	(-1.39)	(-1.31)	(-1.44)	(-0.11)
Stock-market knowledge	0.37	0.35	0.022	0.048
	(0.04)	(0.07)	(0.00)	(1.40)
Trading Experience	-12.30	-6.50	-5.793	-0.015
	(-0.70)	(-0.76)	(-0.64)	(-0.27)
Constant	-127.30	-58.40	**-68.89***	0.244
	(-1.55)	(-1.47)	**(-1.68)**	(0.90)
N	169	169	169	175
R^2	0.17	0.17	0.16	0.16
F-stat	**4.46*****	**4.07*****	**4.51*****	**3.31*****

t statistics in parentheses
$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

Figure 1 *Chart of time series of stock prices. From the chart above the trading software automatically generates the first 4 periods to give an idea about the stocks trend.*

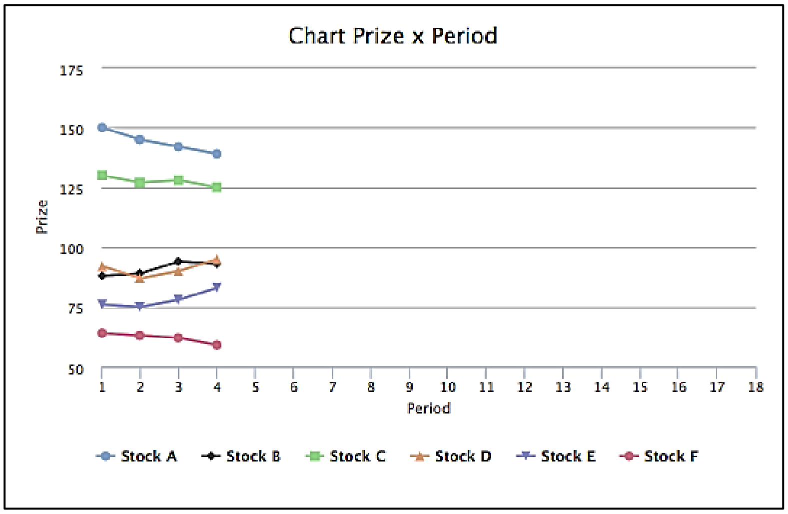
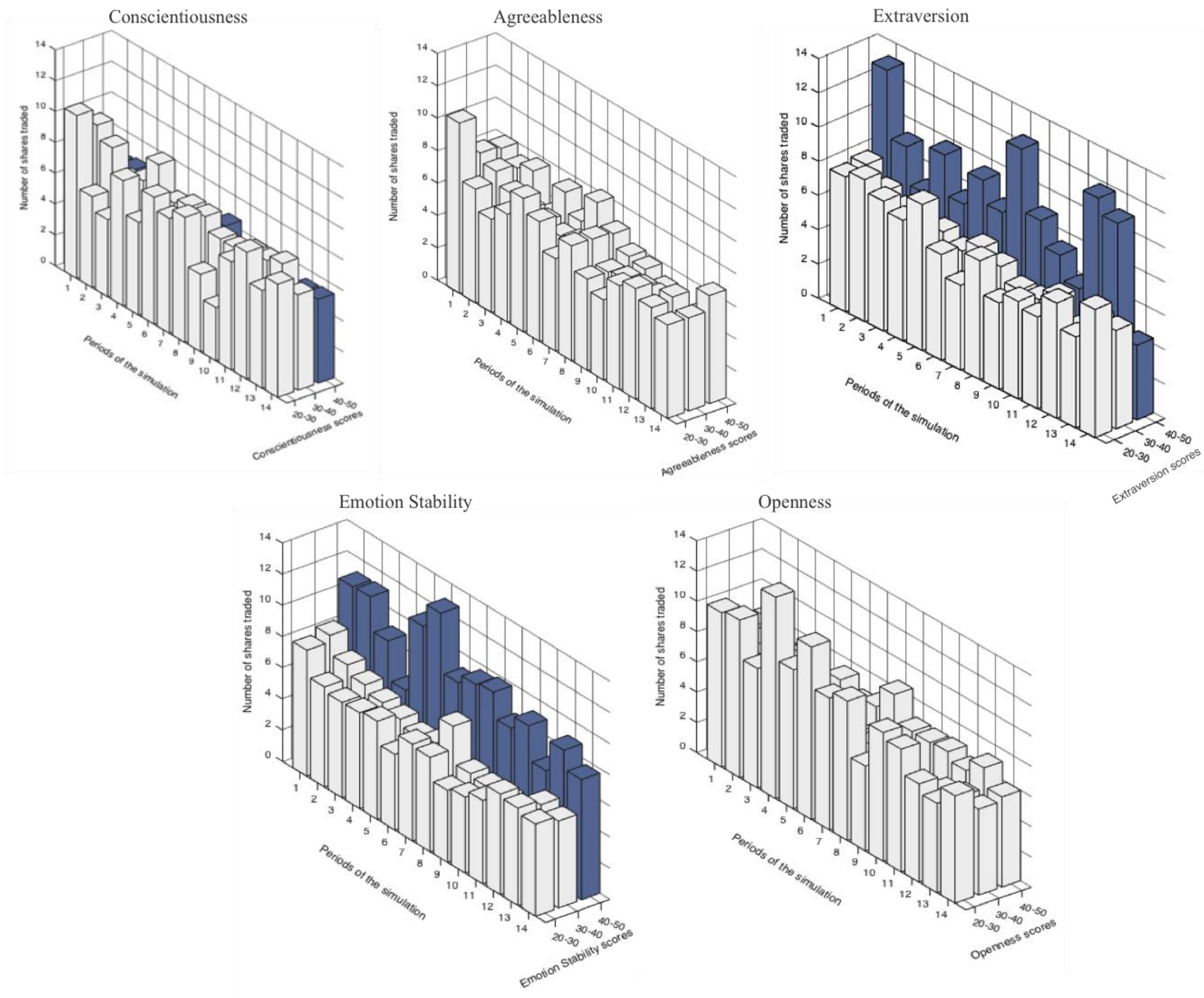


Figure 2 *3DChart of number of stocks traded by participants during all the simulation for each personality trait. On the X axis the personality traits raw scores are aggregated in 5 ranges [0-10; 10-20; 20-30;40-50], Y axis is the periods of the simulation while in the Z axis we plot the number of stocks traded. We exclude ranges for which we record less than 5 observations. Highlighted bars show statistically different values between the personality ranges.*



Appendix

Table 1: *T-test statistics. The table illustrates t-test statistics for the average number of the stocks traded during the last three periods of the simulation among two subsamples: participants with low performances (25% percentile) and participants with high performances (75% percentile).*

	Obs	Mean	Std.Error	Std. Deviation	Minimum	Maximum
Low return group (0)	43	11.75	1.57	10.34	8.57	14.94
High return group (1)	41	11.24	2.42	15.52	6.34	16.14
Combined	84	11.50	1.42	13.05	8.67	14.34
Difference		0.51	2.86		-5.18	6.21
Diff = mean (0) – mean (1)		t = 0.18		d.f. = 82	Ho : diff = 0	
Ha:diff<0		Ha:diff!=0			Ha: diff >0	
Pr(T<t) = 0.57		Pr(|T|>|t|) = 0.85			Pr(T>t) = 0.42	

Table 2: *T-test statistics. The table illustrates t-test statistics for the difference between the average number of the stocks traded during all and the last three periods of the simulation for two subsamples: participants with high performances (75% percentile_Panel A) and participants with low performances (25% percentile_Panel B).*

	Obs	Mean	Std.Error	Std. Deviation	Minimum	Maximum
Panel A - High return subsample						
Number of stocks traded (last three periods)	41	11.24	2.42	15.52	6.34	16.14
Number of stocks traded	41	63.49	7.38	47.29	48.56	78.42
Difference	41	-52.24	5.84	37.39	-64.05	-40.44
t-test = -8.94		Degrees of freedom = 40				
Ha: mean(diff) ! = 0 Pr(|T|>|t|) <= 0.0000				Ha: mean(diff) > 0 Pr(T>t) = 1.0000		
Panel B - Low return subsample						
Number of stocks traded (last three periods)	43	11.75	1.57	10.34	8.57	14.94
Number of stocks traded	43	51.85	3.92	25.71	43.93	59.76
Difference	43	-40.09	2.80	18.37	-45.74	-34.43
t-test = -14.31		Degrees of freedom = 42				
Ha: mean(diff) ! = 0 Pr(|T|>|t|) <= 0.0000				Ha: mean(diff) > 0 Pr(T>t) = 1.0000		

Table 3 *Regression table: Trading volume. A set of OLS regressions in explaining the differences in the amount of securities traded during the simulation is presented The dependent variable is the number of stocks traded The independent variables include the personality traits (extraversion, conscientiousness, emotion stability, agreeableness and openness), demographics data (age, gender, education, stock market knowledge and trading experience) and a measure of risk attitude (DOSPERT). Age is the age of the experiment's participant. Gender is a dummy variable taking values of 0 if male and 1 if female. Graduate is a dummy variable taking the values of 0 if the participant is an undergraduate student and 1 if she is a graduate student. Stock market knowledge is a dummy variable taking value of 0 whether participant has not knowledge on financial markets and 1 if she has a background education in finance or if she works/worked for stock-market services. Finally, trading experience takes the following values: 0 if the participant has low or no trading experience and 1 if she invested at least for one year.*

	(1) Number of stocks traded	(2) Number of stocks traded	(3) Number of stocks traded	(4) Number of stocks traded
Extraversion	9.799			6.78
	(1.81)			(1.18)
Conscientiousness	-11.11**			**-9.21***
	(-2.17)			**(-1.95)**
Emotion Stability	10.93**			7.61
	(2.32)			(1.46)
Agreeableness	1.011			0.23
	(0.21)			(0.06)
Openness	2.883			1.42
	(0.47)			(0.23)
DOSPERT		2.92***		**1.844***
		(2.87)		**(1.71)**
Age			**8.67****	**7.879***
			(2.32)	**(1.89)**
Gender			**39.04*****	**24.91****
			(3.84)	**(2.04)**
Graduate			-27.76*	-22.43
			(-1.92)	(-1.39)
Stock-market knowledge			-1.67	0.37
			(-0.17)	(0.04)
Trading Experience			-8.58	-12.30
			(-1.44)	(-0.70)
Constant	86.03**	33.84		-127.30
	(13.61)	(1.66)		(-1.55)
N	176	169	169	169
R^2	0.04	0.05	0.12	0.17
F-stat	**2.53****	**8.23*****	**3.70****	**4.46*****