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Individual Differences in the Disposition Effect

Keywords: disposition effect; personality traits; realization utility theory; five factor model; financial trading.

Summary: We investigate the disposition effect building on Realization Utility Theory and Big Five Model. Our experimental analysis, combining NEO IP-R personality measures with individual financial data from a trading simulation run by 230 individuals, shows that the disposition effect is driven by two distinct psychological processes, one related to holding losers and the other to selling winners. These two behavioral mechanisms are uncorrelated and influenced by different personality traits.

Abstract

We model the role of personality traits in explaining the disposition effect building on Realization Utility Theory and Big Five Model and moving from an aggregate level to inter-individual differences. Our experimental analysis, combining NEO IP-R personality measures with individual financial data from a trading simulation run by 230 individuals in China and Italy, shows that the disposition effect is driven by two distinct psychological processes, one related to holding losers and the other to selling winners. These two behavioral mechanisms are uncorrelated and influenced by different personality traits. Controlling for different demographic variables we show: 1) a greater sensitivity of the rewarding system that motivate “extroverts” to quickly sell the stock at gain in order to receive a burst of utility; 2) a tendency for “conscientious” subjects to suppress impulsivity, patiently waiting for higher cumulative returns; 3) the importance of “openness to experience” to better value information to achieve higher outcomes.

1. Introduction

Over the last thirty years, an extensive body of literature has shown the effects of cognitive and behavioral biases on financial decisions. Several studies have documented the so-called disposition effect, when individuals tend to cash in quickly financial gains but hold on longer on trades at loss (Shefrin and Statman 1985; Weber and Camerer 1998; Odean 1998; Frazzini 2006). Yet, we still lack a clear understanding of what drives it and how different trading styles impact the formation of its determinants. Most of the previous studies have looked at the disposition effect at an aggregate level of analysis, masking considerable cross-section variation in the understanding of investors’ behavior (Odean 1999).

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3 Moreover, theoretical models based on information asymmetry or transaction costs have failed to give an
4 interpretation of the heterogeneity in the tendency to ride losers and sell winners (Odean 1998).

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6 Finding a relevant explanation of the roots of the disposition effect is crucial, as the bias is clearly
7 an investment mistake that leads to underperformance in a wide class of investors (Odean 1998; Dhar and
8 Zhu 2006; Frazzini 2006). Following interdisciplinary approaches, which link decision-making under risk
9 and psychological factors (e.g. Lauriola and Levin 2001), we model the role of personality traits as
10 determinants of individual differences in the disposition bias. As in Durand et al. (2013), we use the Five-
11 Factor Model (FFM, Tupes and Cristal 1961) where the personality is categorized in five broad
12 dimensions: extraversion, conscientiousness, neuroticism, agreeableness and openness to experience. As a
13 stable pattern of behaviors and cognitions (Fleeson 2001), personality traits contribute to explain
14 individual choices in a financial setting. The stimuli given by each of the five traits in altering the attitude
15 towards gains and losses justify the variation in the disposition effect level among investors with different
16 personality profiles. In particular, we expect that a financial cue engages processes based on the
17 underpinnings of personality (mainly reward/punishment system, impulsivity and seek for novelty), with
18 extroverts exhibiting a greater propensity to sell winners compared to losers, neurotics postponing selling
19 operations of stocks at loss, and conscientious and open investors holding longer before closing positive
20 positions instead of negative.
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31 We empirically test our model through a cross-sectional experimental analysis in a sample of 230
32 students of Economics at the University of Bologna (Italy) and at the University of Wuhan (China).
33 Subjects participated in a trading competition based on Weber and Camerer (1998) experimental task and
34 were profiled according to the Big Five personality traits measures and their demographic characteristics.
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37 Our results show that extroversion is positively associated with the disposition effect, while
38 subjects with high conscientiousness and openness to experience are less biased. In line with the
39 psychological literature that demonstrates a link between extraversion and high sensitivity to reward
40 (Smillie 2013) we report that extroverts prefer short-term capital gains instead of delayed profits (Daly et
41 al. 2009). Moreover, the fact that in our experiment open mind investors close negative positions faster
42 than positive ones offers specific support for the role of the facets of intellect, curiosity and exploration in
43 reducing harm-avoidance behavior through unconventional decision-making (Costa and McCrae 1992;
44 Lauriola and Levin 2001). Finally, we show how low impulsive investors base their trading activities on a
45 non-immediate aim-achievement leading them to follow long-term strategies for the main goal of higher
46 returns (Daly et al. 2009).
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53 This paper offers several theoretical, empirical and practical contributions. First, we build on
54 previous literature in psychology and finance demonstrating the role of personality traits in explaining the
55 disposition effect. Although Durand et al. (2013) first investigate the relationship between the personality
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3 traits and the disposition effect, in this study we offer a more comprehensive analysis of the cognitive
4 mechanisms, behind each trait, able to affect investor financial decisions in the domain of gains and
5 losses. We leverage on a larger and more heterogeneous group of individuals in terms of nationality. In
6 fact, our sample includes subjects from China and Italy that leads us to take into account differences in
7 cultural and social values as potential moderators of the personality' role on the disposition bias.
8 Furthermore, no prior study has put into a theoretical framework the relationship between PT and DE. We
9 propose the Realization Utility Theory and the Five Factor Model as the keys to explain how and which
10 condition certain associations should emerge.

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16 Second, in proposing a study at the individual level, we analyse investment heuristics for each
17 different investor and we detect and monitor data features that are not visible in traditional trading
18 databases. This clarifies the behavioral underpinnings of the disposition effect, giving the opportunity to
19 disentangle the individual decision processes by analyzing directly the moment when wealth changes.

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23 Third, our insights might motivate theorists to accommodate the heterogeneity in personality
24 traits in normative models that capture anomalies in asset pricing and portfolio choice as insufficient or
25 naive diversification (French and Poterba 1991), excessive trading (Odean 1999) and underreaction
26 (overreaction) to the events (Frazzini 2006). Finally, our study can raise the attention of investment firms
27 and financial companies in guiding their recruiting and training practices, as well as that of regulators in
28 educating individuals and help them make better investments.

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34 In the following sections, we first provide a review of the literature on disposition effect and
35 personality traits and develop a set of hypothesis. In Section 3 we present the experimental protocol,
36 while we describe the data and results in Section 4 and 5 respectively. Section 6 discusses the results and
37 presents our conclusions.

38 39 40 41 42 **2. Literature Review**

43 44 *2.1 Disposition Effect*

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46 The attitude to ride losses instead of gains has always represented one of the most challenging trading
47 anomalies to define. Starting from Shefrin and Statman (1985), the disposition effect has been widely
48 investigated both in controlled environments and in market settings. After its first empirical
49 demonstration (Odean 1998; Weber and Camerer 1998) and the evidence of a negative correlation with
50 investment returns (Odean 1998), researchers have shifted their attention to the implication of the
51 phenomenon in financial trading. Grinblatt and Han (2005), Frazzini (2006) and Birru (2015) show how
52 the disposition effect can slow stock-price reaction to new information, while Goetzmann and Massa
53 (2008) demonstrate how the bias is positively (negatively) associated with trading volume (volatility).

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3 Following Dhar and Zhu (2006) and Kumar and Lim (2008) we know that investors that execute more
4 trades have a lower disposition effect, don't exhibit a disposition effect for some stocks (Kumar, 2009)
5 and don't exhibit a disposition effect in mutual funds (Chang et al 2016).
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8 In spite of many efforts to confirm these results and continue to explore the greatest paradoxes of the
9 common financial advice "cut your losses and run your gains", private information, speculation,
10 transaction costs and tax advantages failed to give an interpretation of the disposition effect (Odean
11 1998).
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14 Coming from a different perspective, many economists used the Prospect Theory of Kahneman
15 and Tversky (1979) to show how individuals make decisions based on a reference point (Frydman and
16 Rangel, 2014)¹. According to the Prospect Theory, investors who exhibit disposition effect are risk-
17 averse towards gains while they seek risk when they are experiencing losses. Barberis and Xiong (2009)
18 have discussed the difficulties in formalizing this statement. In particular, when a subject computes his
19 own preferences on annual gains/losses rather than realized gains and losses, he is more likely to observe
20 a positive relation between prospect theory and the opposite of disposition effect. Accordingly, economic
21 models better predict individual investment behavior if utility is derived not only from a total wealth
22 experience (as annual gains/losses or on the entire portfolio) but from every investing episode. Along this
23 line, Barberis and Xiong (2012) in a subsequent paper suggest that investors (especially if individuals
24 rather than institutional) have separated burst of utility for different single events (e.g. "I purchased a
25 share of Ferrari at \$40 and I sold at \$60"). Instead of computing their wealth as the sum of several
26 investments, the amount of utility they experience is positively related to the size of the realized
27 gains/losses on the assets they are trading. The higher the distance between the purchase price and the
28 price at which the stock is sold, the greater the utility burst (*Realization Utility Theory*). Ben-David and
29 Hirshleifer (2012) confirm these results, empirically finding that the disposition effect is driven by the
30 magnitude of the gains and losses experienced by investors instead of a simple direct preference for
31 realizing gains relative to losses. The authors are concerned with overconfidence-driven speculation
32 motive for trades as an explanation for this phenomenon (*Expectation Based Theory*).
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47 ¹The way in which the reference point is evaluated is an on-going debate. Especially, the theories based
48 on narrow framing often use different reference points for the evaluation of gains and losses (risk-free
49 rate, zero return and size of gains/losses). A recent model from Hartzmark (2014) suggests to consider
50 portfolio composition as the key to explain differences in how investors evaluate holding stocks. In
51 particular, the author introduces the rank effect, showing the tendency of the subjects to take selling
52 decisions comparing the trend of the stocks in their portfolio (e.g. closing extremely winning and losing
53 positions).
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However, the **Expectation Based Theory** does not entirely fit with our paper, since, as we present in Section 3, our experimental design excludes any possibilities to speculate or have private information on the securities that participants are trading with.

Therefore, even if there is no unanimous consensus on what is the best behavioural model in predicting the disposition effect, employing the basic ideas underlying other relevant models, for our purposes, Realization Utility Theory offers a convincing framework in the study of the heterogeneity bias among investors (Frydman et al. 2014). This is particularly relevant as the analysis of the phenomenon at an aggregate level masks considerable cross-section variation in the understanding of the trading behavior (Odean 1999). Surprisingly, very few attempts have been made to detect investor characteristics able to explain inter-individual differences in the disposition effect. Besides, to the best of our knowledge, most attempts **just considered demographic and psychological characteristics**. Chui (2010) demonstrated a negative correlation between disposition effect and the trait of locus of control, while Dhar and Zhu (2006) focused on financial wealth, professional occupation and educational background, to demonstrate that “high-income” and “professional” investors display lower disposition effect. These results are later confirmed by Da Costa et al. (2013) who highlight “trading experience” as a driver to reduce disposition behavior, with the students in their sample showing higher level of disposition bias than professionals. **For our reference, Durand et al. (2013) are the first to investigate the relation between the FFM and the disposition effect. Through an experimental analysis, in a sample of 115 students, the authors found a positive association between the traits of agreeableness and conscientiousness with the net realized gains.**

2.2 Personality Traits

In a perfect standardized environment where agents have the same information, experience and knowledge, the variation in decisions made by individuals reflects the differences in the way automatic mechanisms (often unconscious) drive various cognitive processes. Psychological literature (e.g. Fleeson 2001) organizes this heterogeneity in stable patterns of affects, behavior and cognition that take the name of personality traits. Thoughts, emotions, actions are all elements of personality traits (Kassin 2003). Within the wide scientific area embraced by this notion, psychologists, from the seminal work of Allport **in** 1921, started a gold rush to better define and measure the basic traits of human personality.

A long stream of theories succeeded over the years defining them as **stable** over time, different across subjects and able to influence **people's** behavior. A long stream of efforts developed measurement scales to provide a better picture of human complexity. Tupes and Christal' five-factor model (1961), in particular, defines the basis of Big-Five with neuroticism, extraversion, conscientiousness, openness to experience and agreeableness describing the key psychological characteristics of individuals. The model has the advantage to take into account, for each trait, various **non-overlapping** dimensions. For example,

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3 sub-levels of neuroticism include the tendency to experience unpleasant emotions like anxiety, fear and
4 anger. Table 1 provides a detailed description of lower dimensions for the five personality factors.
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12 The heterogeneity of the resulting psychological constructs beyond each of the five traits is also
13 the main criticism directed at the Big Five model (Boyle 2008). The fact that the underlying
14 psychological processes of each trait are not always orthogonal (Saucier 2002) raises concerns about the
15 Big Five construct validity. However, the Big Five model appears to show consistency in describing
16 normal personality trait sphere and its structure seems to find reliability across ages and cultures (Schacter
17 et. al 2011).
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21 The accuracy of the Big-Five theory is widely accepted in psychological literature and the
22 assessment of each trait takes place mainly through self-reported questionnaire. Several studies
23 established substantial evidence in using these personality measurements to explain heterogeneity across
24 population. From caffeine consumption to learning process, social psychologists employed the
25 questionnaire to analyze an endless list of behaviors, often combining various research fields (Ozer and
26 Benet-Martinez 2006). Since their role in the **understanding of** individual differences in subjects'
27 cognitive, emotional and motivational processes, the traits result as the key to detect the differences
28 across subjects in decision-making.
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37 *2.3 Disposition Effect and Personality Traits*

38 Some researchers have started to analyse the effect of personality traits on financial decision making (e.g.
39 Fenton-O'Creevey et al. 2004; Grinblatt and Keloharju 2009; Grinblatt et al. 2011; **Durand et al. 2013**;
40 Conlin et al. 2015). This paper leverages on Frydman et al. (2014), who use neural networks to test the
41 reliability and the implications of the Realization Utility on the disposition effect. In particular, in
42 describing the cognitive process behind the Realization Utility, they clearly identify several key
43 psychological constructs that might affect individual investment behavior as they state: "*If an investor
44 derives pleasure from realizing capital gains and, moreover, is impatient, he will be keen to sell stocks at
45 a gain. Conversely, if he finds it painful to sell stocks at a capital loss and also discounts future utility at a
46 high rate, he will delay selling losing stocks for as long as possible.*"
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53 Let's focus on the differences in the way subjects respond to positive and negative stimulus, i.e.
54 the rewarding and punishment sensitivity (Eysenck 1967) and consider a scenario where subject A and
55 subject B have the same stock i in their portfolio. If subject A is more sensitive to rewards than B and an
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3 increase in the price of stock i from its purchase level occurs, subject A may ascribe more value to that
4 capital gain than subject B. The distance in how the value is encoded could lead the two individuals to act
5 differently. In particular, we should expect that being more sensitive to rewards, subject A will be more
6 likely to sell the stock at gain faster than B and *vice versa*. Moreover, the fact that in some cases rewards
7 and punishments are considered reinforcers, could amplify their influence on individual investment
8 behavior increasing the probability that the subject will behave consistently to obtain the same output.
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13 However, the clear effect on the realization utility and consequently on the disposition effect, is
14 not exclusive to reward and punishment sensitivity. The same relationship can also be interpreted looking
15 at another psychological construct, i.e. the impulsiveness trait, which is underpinning a greater sensitivity
16 to rewards (Eysenck 1967; Torrubia et al. 2001) and that leads subjects to act with little or no concerns for
17 future consequences (VandeBos G. 2007). These two elements combined depict an impulsive individual
18 who, acting with small regards about her behavior, sells stocks as soon as a capital gain occurs. While
19 being impulsive might drive differences in the gain' side of the disposition effect, in the realm of losses,
20 the traits of anxiety, and **more generally** of neuroticism, is at the base of a negative relationship with the
21 bias among investors. Indeed, in experiencing an increase reaction to negative signals (Eysenck 1967;
22 Torrubia et al. 2001), a neurotic might **not sell the stocks quickly at a loss** waiting for possible price
23 increases that could reduce their unpleasant feelings.
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31 The list of psychological facets that may affect the individual utility formation, and **in turn the**
32 financial decisions, is long and straightforward. Reward/punishment sensitivity, impulsiveness and
33 anxiety are just three constructs of broader dimensions that see systematic interactions among multiple
34 factors (as extraversion, sensation seeking, conscientiousness, intellect and openness - Costa and McCrae
35 1992). Therefore, in analyzing the impact of the psychological variables on the disposition effect, we need
36 a framework proposing a complete and clear categorization of the personality profile. The Five-factor
37 model (Tupes and Christal 1961) answers our needs and in the next paragraph we use it to model the
38 relation between the personality traits and different levels of disposition effect.
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45 *2.4 Big Five Model and the Disposition Effect*

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47 During the last years, scholars identified relevant correlations between big five personality dimensions
48 and risky behavior (Lauriola and Levin 2001; Nicholson et al. 2005; Lo et al. 2005; Mishra and Lalumiere
49 2011). Unfortunately, the results are limited to the parametrization of risk-taking level for specific
50 domains (health, financial, career, social, safety and recreational risk), and empirically it remains hard to
51 explain the difference in the magnitude of the correlation between personality traits and risk-preferences
52 reported by studies relying on experimental design and those based on self-reported questionnaire.
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3 Although these limitations do not help in showing evidence of a stable pattern among personality traits
4 and decision-making under uncertainty, some attempts have been made to detect which personality traits
5 relate to real financial decisions. Conlin et al. (2015) document a positive association between the
6 dimension of extraversion with the stock-market participation in terms of the number of securities (debt
7 and asset) held by the investors. Moreover, in a sample of 118 investment bankers, Fenton-O’Creevey et
8 al. (2004) find that high openness to experience and both low extraversion and neuroticism significantly
9 correlate with better trading performance. Grinblatt et al. (2011) use a Finnish dataset to match individual
10 trading records to a measure of intelligence (IQ), one of the main elements of openness to experience
11 (Harris, 2004). Coherently with the findings of Fenton-O’Creevey et al. (2004), they show that
12 intelligence predicts lower levels of disposition effect and high returns. In the opposite direction are the
13 results from a previous work of Grinblatt and Keloharju (2009), who study the effect of sensation seeking
14 in altering individual investment choices. An individual who scores high on sensation seeking exhibits
15 preferences for adventure sports, drugs intake and illegal activities, and the trait has been always
16 attributed to impulsive and extraverted subjects (Eysenck 1990; Zuckerman 1969). In particular, Grinblatt
17 and Keloharju (2009) point out how sensation seeker investors show higher level of trading activity but
18 exhibit higher levels of negative returns.

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21 Finally, Durand et al. (2013) are the first to analyze a relation between the FFM and disposition
22 effect. The authors found a positive association between the traits of agreeableness and conscientiousness
23 with the net realized gains. While the results from Durand et al. (2013) demonstrate a relation between
24 disposition effect and personality, in the next paragraphs we focus on the behavioral mechanisms, behind
25 the traits, able to explain how and which conditions the personality affect the disposition effect, both in
26 the domain of gains and losses.

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29 To analyze the effect of four of the Big Five personality trait on disposition effect, we start from
30 the cognitive underpinnings of the traits to depict the most frequent behaviors of a given personality
31 profile. These behaviors/preferences are then linked to expected trading strategies that the subjects will
32 adopt in line with their psychological characterization. Following Dhar and Zhu (2006) and Frydman et
33 al. (2014), who document the absence of a correlation between selling winners and holding losers, and in
34 line with the previous literature on personality and risky choices (Kahneman and Tversky 1979; Lauriola
35 and Levin 2001), we then model how investment operations influence the levels of disposition effect
36 among individuals and whether these changes are more pronounced in the gain or loss domain. We will
37 not develop any hypothesis for the trait of Agreeableness as there is no evidence of any relationship with
38 decision-making attitudes (Barrick et al. 2002),

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41 Since the seminal work of Depue and Collins (1999), extraversion has been increasingly linked to
42 reward systems (Smillie 2013; Fletcher, 2013) showing how extroverts enjoy more intensely rewarding

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3 situations than other individuals (Costa and McCrae 1992). This excitement in obtaining immediate
4 rewards over delayed rewards (Daly et al. 2009), a key facet of extraversion (Eysenk 1967; Zuckerman
5 1969; Aluja et al. 2003), determines the monetization of capital gains as soon as they appear. After a burst
6 of utility in experiencing a reward, extroverts usually reinforce the positive value ascribed to an
7 object/behavior/status increasing the likelihood of repeating previous actions to reach similar appetitive
8 goals. With respect to a raise in a stock price from its purchase level, the greater sensitivity to capital
9 gains might motivate extroverts to quickly sell the stock every time a potential short-term profit shows up.
10 The dependent trading pattern that results from this strategy could further strengthen the probability for
11 these investors to record higher disposition effect. We can therefore hypothesize the following:
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19 Hypothesis 1. *Extraversion is positively related to the magnitude of the disposition effect through the side*
20 *of gains.*
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24 In the realm of losses, while psychological theories predict null or negative low correlation
25 between extraversion and sensitivity to punishment, a positive high relation with neuroticism has been
26 highlighted (Zuckerman et al. 1999; Torrubia et al. 2001). In particular, Larsen and Ketelaar (1989) show
27 how neurotic individuals exhibit an amplified reactivity just to punishment-induced affects but not to
28 positive cues. The sub-trait of anxiety acts as the main dimension in pushing people to respond strongly
29 to negative signals and to avoid behaviour that might result in negative outcomes. A decrease in the stock
30 price is a typical non-reward experience that investors face during their trading session and can lead
31 neurotic individuals to not close rapidly loss positions. Indeed, these subjects are highly inclined to
32 postpone the monetization of their capital losses, gambling on potential price' increases that could reduce
33 their hurtful feelings. We can therefore hypothesize the following:
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42 Hypothesis 2. *Neuroticism is positively related to the magnitude of the disposition effect through the side*
43 *of losses.*
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47 Conscientiousness is usually a good predictor of high individual job/academic performance
48 (Almlund et al. 2011; Burks et al. 2015) since, according to Costa and McCrae (1992) is composed of
49 different constructs that lead people to act dutifully and efficiently. In particular, conscientious subjects
50 tend to suppress impulsivity working for goals (even monetary) that are not immediate (Daly et al. 2009).
51 Along with the self-discipline construct that is implicated in the attitude to make sacrifices in order to
52 obtain higher rewards, the trait of conscientiousness underlies the ability to anticipate future outcomes
53 from current choices. This capacity allows subjects to temporally discount the potential payoff over time
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3 horizons and to alter their emotional response in favor of more convenient and less biased decisions
4 (Camerer 2008). From the analysis of this trait, we thus expect that a non-impulsive investor might
5 simply not sell stocks at the first gains, patiently waiting for higher cumulative returns even if it would
6 mean to support some losses during the trading pattern. We can therefore hypothesize the following:
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11 Hypothesis 3. *Conscientiousness is negatively related to the magnitude of the disposition effect through*
12 *the side of gains and losses.*
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16 Openness to experience drives to better job performance in a similar manner to conscientiousness, but
17 through different processes and with higher intensity (Almlund et al. 2011). This trait underlies the main
18 sub-dimensions of intellect, curiosity, imagination and exploration, and it is possible to recognize how
19 openness to experience uses different cognitive channels to affect successful decision-making. Although
20 subjects who score high on this trait do not always outperform the less open counterparts, they are better
21 at activating learning orientation toward higher long-term knowledge and skill acquisition (Rolfhus and
22 Ackerman 1999). Being very interested in what surrounds them, high open individuals also enjoy trying
23 different approaches to doing things (Costa and McCrae 1992). In particular, Costa and McCrae (1992)
24 show how this trait leads subjects to be less categorical in ideas and more willing to accept novelty. They
25 are less locked into pre-conscious mechanisms and this reduces their chance to repeat dependent and
26 harm-avoidance behaviors and allows them to act differently every time something new occurs. When
27 they engage in decision-task with reward, open persons have more sensitivity not to the reward itself but
28 to the value of information that they can use to yield positive outcomes. The adaptability in new context
29 leads subjects who score high on openness to experience taking better decisions (Le Pine et al., 2000). In
30 a trading perspective, whereas the facet of intellect guides to a general learning predisposition and
31 superior investment performances (Grinblatt et al. 2011), we might expect a less biased strategy in
32 subjects who score high on openness experience. Especially, following the characterization of the trait in
33 the gain and loss domains (Lauriola and Levin 2001), we could observe slower closing activities for
34 positive positions rather than negative. We can therefore hypothesize the following:
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49 Hypothesis 4. *Openness to experience is negatively related to the magnitude of the disposition effect*
50 *through the side of gains and losses.*
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54 Table 2 summarizes the different hypotheses for Extraversion, Emotion Stability, Conscientiousness and
55 Openness.
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Insert Table 2 about here

3. The Experimental setting

Following a long and established tradition in decision-making research, we built an experimental design where individuals react to well specified investment settings. Using personality inventory surveys as well as trading simulations, we construct measures of personality traits for each subject, and we correlate these measures with trading records. Building on the findings of individualism-collectivism cultural differences (Triandis 2001), we selected our individuals with a cross-country empirical setting to increase the variation of personality traits in our observations. This point is relevant because a heterogeneous reduced amount of subjects might not promptly catch the effect of personality sub-dimensions (Lo et al. 2005). We therefore engaged 234 undergraduate and graduate students between the ages of 19 and 31, 176 from the School of Economics of the University of Bologna (Italy) and 54 from the School of Economics of the University of Wuhan (China). Volunteers were gathered through announcements during lectures, where students were told that a trading contest would be conducted by the Department of Management of the University of Bologna.

Before the experiment started, all participants were asked to complete a questionnaire collecting socio-demographic variables that are known to be associated with the disposition effect (age, gender, education, stock-market knowledge and experience), as well as the International Personality Item Pool (IPIP) NEO which has been calibrated with responses from over 20,000 individuals (Goldberg 1999). Based on these calibrations and considering our setting, we used the 50-item public-domain version which can typically be completed within 5–10 minutes (<http://ipip.ori.org>). The questionnaire reports 10 items for each of the big five personality dimensions: (1) Extraversion; (2) Agreeableness; (3) Conscientiousness; (4) Emotional Stability and (5) Openness to Experience. Participants describe themselves using a 5-point scale varying between disagreement (1 = very inaccurate) or complete agreement (5 = very accurate). After completing the questionnaires, the subjects were engaged in a trading simulation. The experiment was completely anonymous as all booking and informational communications were done through numerical codes as a unique identifier for each subject.

The trading game software was based on the Weber and Camerer (1998) experiment. Participants have the chance to trade 2000 € for 14 periods in six risky assets, generally labelled from A to F to avoid the potential effect of different asset classes on the disposition effect (Chang et al. 2014), and with stock prices randomly generated and not affected by the subjects' trading actions. Individuals monitor 5 types of stocks which vary according to the changes of a price-increasing/decreasing sequence as reported in Table 3 and with an absolute variation of the stock price between 1 and 5 Euro. Participants are instructed

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3 about the probabilities of all six assets to rise and fall, but they are not aware of share-probability scheme
4 matching. A short tutorial has been provided at the beginning of each experiment.
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7 Even if there is a long-established literature in behavioral finance using students as experimental
8 subjects, (e.g. Weber and Camerer, 1998; Bassi, Colacito and Fulghieri, 2013; Durand et al., 2013;
9 Frydman et al., 2014; Frydman and Rangel, 2014), the limitations of a non-professional cohort (e.g. Bello
10 et al., 2009 and Peterson and Merunka; 2014) leads us to carefully control for potentials external validity
11 issues. In particular, participants were incentivized to perform well during the experiment. In real life, the
12 career and wealth of a trader depend directly by their financial outcomes. For the participants in this
13 study, their success in the competition, depends on their performance in the trading simulation. The
14 competition had a total worth of €330,00 each session, therefore all the subjects had strong incentives to
15 perform the best they could. In particular, the reward system has been set on the highest realized gain.
16 The best performer receives a total prize of 165€, the runner up 100€, the third and the fourth 50€ and
17 15€, respectively.
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20 Finally, all students were informed that the chance to win the prizes was based also on the
21 accuracy in answering the queries in the questionnaire. In case of clear random answers or inconsistency,
22 the financial records from the participant would not be considered for the final rewards.
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31 *Insert Table 3 about here*
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34 The simulations begin with the software automatically generating the first 4 periods to provide
35 the participants with the initial stock price path. Figure 1 illustrates an example of the stock prices
36 evolution showed in the main screen of the simulation website.
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41 *Insert Figure 1 about here*
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44 Participants then trade for 14 periods of maximum 2 minutes each and the software takes the
45 participant automatically to the next trading period after the 2 minutes, unless the participant decides to
46 move early to the subsequent period. A short 4-period trial session of the simulation is provided to allow
47 participants to familiarize with the software. Our final data set contains trading records from various
48 experimental sessions run between May 2014 and November 2014. We excluded 4 participants who
49 executed only buying trades during the simulation, thus leaving us with a total of 230 individuals. The
50 voluntary basis of the participation in the trading competition lead us to experience unbalanced
51 observations in terms of gender (90 females vs. 140 males) and country origin (176 Italian vs. 54 Chinese)
52 which is accounted for in the analyses.
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4. Data

4.1 Summary Statistics: Demographics and Personality Traits

Table 4 reports summary statistics of demographics and personality traits for our entire sample. Age varies between 19 and 31, with a mean value of 22. 112 participants were undergraduates, 111 graduates and 7 subjects had just passed their master diploma and were enrolled in PhD courses. As for their stock market knowledge, 119 participants declare that “My field of education is not related to trading in investment instruments, neither I hold/held a job position in this field”, 107 that “Only my education is related to trading in investment instruments” and just 4 subjects answer “In the last ten years I held/or I hold a job position in the financial sector”. Finally, as for their trading experience, 193 have never invested before, 17 have traded once a year, 11 once every three months and only 9 every month.

On average participants scored 33.66 on extraversion, 38.18 on conscientiousness, 30.97 on emotion stability, 35.31 on agreeableness and 37.17 on openness. We compared these findings with what reported by McAdams and Donnellan (2009). The authors used the IPIP to measure the personality scores for a large sample of first year students at a large university (n=529).

Their results were: extraversion 35.1, conscientiousness 36.3, emotion stability 32.0, agreeableness 36.6 and openness 33.8. The scores of our cohort are in line with the research of McAdams and Donnellan (2009), in particular, our results are slightly higher on conscientiousness and openness and lower on extraversion, emotion stability and agreeableness.

In line with previous literature on gender differences among personality traits (Feingold 1994), females score higher on conscientiousness than males ($p < 0.01$). Men and women seem to differ also on emotion stability, where females score lower than males ($p < 0.01$). No statistically significant differences in the personality traits raw scores are found between Chinese and Italian subjects. These results lead us to consider our sample as quite homogeneous, even with respect to trading experience and knowledge, and they seem to suggest a personality profile for subjects who want to engage or are interested in trading activities.

Insert Table 4 about here

Table 5 reports the correlation coefficients and we can see that the sign of the pairwise correlations among personality traits are coherent with the results of the meta-analysis on 212 Big Five studies conducted by Van der Linden et al. (2010), except for the one between agreeableness and extraversion which is here negative instead of positive. Gender has a positive significant correlation with

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extraversion (0.17 p<0.01), emotion stability (0.22 p<0.01) and openness to experience (0.18 p<0.01). Consistent with the evidence of higher academic performance for conscientious subjects (Almlund et al. 2011), conscientiousness relates with the level of education positively (0.22 p<0.01) while negatively with the knowledge on financial markets. The level of knowledge of financial markets has also a negative correlation with the traits of extraversion (-0.14 p<0.05), emotion stability (-0.13 p<0.05) and a positive one with trading experience (0.14 p<0.05). Finally, the correlation between openness to experience and trading experience is positive (0.17 p<0.01).

Insert Table 5 about here

4.2 Summary Statistics: Disposition Effect

Following Odean (1998) the level of disposition effect varies between -1 and 1 and is computed as the difference between the Proportion of Gains Realized (PGR) and the Proportion of Losses Realized (PLR). PGR (PLR) are expressed as a ratio of realized gains (losses) over the sum of paper and realized gains (losses).

$$DE = PGR - PLR \quad (1)$$

where PGR and PLR are respectively:

$$PGR = \frac{\text{Realized Gains}}{\text{Realized Gains} + \text{Paper Gains}} \quad \text{and} \quad PLR = \frac{\text{Realized Losses}}{\text{Realized Losses} + \text{Paper Losses}}$$

For paper gains or losses, the reference is the number of securities not sold in the portfolio. Whether there will be a paper gain or loss is determined by comparing the high and low price for that day/period with the purchase price. If the disposition effect level is greater than 0 (PGR ratio is greater than PLR) the investor is selling winners too soon and/or holding losers too long, and vice versa if it is smaller than 0 (PGR ratio is smaller than PLR). When the disposition effect equals to 0 (PGR is equal to PLR) the investor ascribes the same value to gains and losses and he is indifferent in closing/riding capital gains or losses.

Insert Table 6 about here

Table 6 reports summary statistics for the disposition effect levels among our sample of 230 subjects. The mean of PGR, PLR and DE are 0.36, 0.34 and 0.02, respectively. As from Figure 2, in

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3 which we present the distribution of the DE, almost 45% of individuals do not exhibit DE or reveal an
4 opposite behavior to the disposition bias.
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11 Compared to previous research (e.g. Weber and Camerer, 1998), the shorter time-frame of our
12 experiment is a potential explanation for the lower disposition effect level of our sample. Following the
13 main proposition of Dhar and Zhu (2006) where the trading frequency negatively correlates with DE
14 levels, in Table 6 we find that subjects who trade less frequently are more inclined to DE bias. In
15 particular, we believe that the reduced time in which participants could trade pushed them to amplify the
16 number of operations performed. In our sample, we show on average high frequency in the trading
17 activities performed by the participants. The mean of the not-invested cash during the simulation is
18 505.42 € and the number of trades executed by the subjects is 26 (around 2 operations for each period). In
19 preferring higher trading frequency, on average students monetize capital gains when they experience a
20 3% positive return and they usually close negative positions with a 2.2% negative return.
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27 Another potential motivation for the documented low DE level might be that the experiment
28 rewards only the top performers, leaving no different payoffs to the remaining participants. In particular,
29 subjects with low performances might be encouraged to change their trading behaviour in the last periods
30 of the simulation, taking more risk as a final chance to increase the returns and win a prize without losing
31 anything. Indeed, these investors might be prone to close rapidly all their negative positions, betting the
32 available budget on the current winners until the end of the simulation. This strategy, increasing the
33 number of realized losses and the number of paper gains would in turn reduce the disposition effect. We
34 test for this potential bias comparing the investment behaviour between subjects with low and high
35 performances. We analyse whether the two subsamples differ in the trading activities performed next to
36 the end of the simulation (last three periods) with respect to the investment style followed during all the
37 simulation session, but we did not observe any statistically significant difference. During the last three
38 periods of the simulation, the entire sample exhibits a tendency to reduce the number of stocks bought,
39 while no differences are highlighted in the quantity of stocks sold and in the type of stocks traded, and
40 low performance subjects keep their investment strategy stable over time.
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50 In line with previous works (Dhar and Zhu 2006; Frydman et al. 2014) PGR and PLR show a
51 negligible and non-significant correlation (0.115) confirming that the variation in the disposition effect
52 among investors is better understood as a combination of separate psychological mechanisms governing
53 selling behaviors in case of gains and losses. Consistently, Figure 3 shows how subjects who exhibit an
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3 attitude to quickly close positions at gains do not necessarily behave in the same way in the loss domain.
4 Similarly, those who delay cash gains unlikely ride longer positions at loss.
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11 While we do not find any association between DE and gender, age and cross-country differences,
12 disentangling the two components of the DE, we notice that Chinese sells more losers and winners stocks
13 than Italians ($PLR_{China}=0.46$; $PGR_{China}=0.48$; $PLR_{Italy}=0.30$; $PGR_{Italy}=0.32$; $p<0.001$). This result is in line
14 with Statman (2008), who investigates the impact of cultural differences in the approach to investing,
15 conducting a survey over 22 countries and over 4000 subjects to analyze how different religious, social
16 and ethic belief/values affect the individual risk-preferences in a financial setting. This paper shows that
17 people from more individualistic countries (Italy, Israel, United States, UK, Germany, Norway and
18 Switzerland) are more risk-averse than those from collectivistic regions such as China, India, Vietnam,
19 Taiwan but also France and Holland. In explaining **this insight**, the author relates to the “cushion
20 hypothesis” introduced by Hsee and Weber (1999), in which the higher risk propensity in collectivistic
21 societies is driven by a strong group-cohesion leading individuals to feel protected (safe cushion) in case
22 of failure and that **motivates** their higher trading activity.
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32 *4.3 Bayesian Optimal Trading Strategy*

33 We now characterize the optimal trading strategy for a risk-neutral Bayesian investor whose objective is
34 to maximize the expected value of his earnings. According to Weber and Camerer (1998): *“The optimal*
35 *Bayesian method corresponds to a simple heuristic way to judge which of the six stocks has which trend:*
36 *count the number of times a share rose in price. The share with the most price increases is the most likely*
37 *to have the trend ++; the share with the second highest number of price increases is most likely to have*
38 *the trend +, etc.”* Therefore, an investor who uses a Bayesian optimal strategy will count at period 4 (the
39 beginning of the experiment) the number of times each share rose in price and then will select the stock
40 (or the stocks) with the highest number. For each period after the fourth, the investor will update his count
41 and, based on that, he will adjust his portfolio composition.
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49 For example, if at period 4 (at the beginning of the experiment) we observe that stocks “A” and
50 “B” have risen in price 3 times, “C” and “D” only 1 time while “E” and “F” have only dropped in value,
51 we may imply that stock “A” or “B” or both are more likely to have a ++ trend. Building the investment
52 strategy on this heuristic, the expected-value subject will only equally invest in stock “A” and “B”.
53 Suppose that at period 5 “A” shows a price increase while B exhibits a downturn. Now stock “A” has the
54 highest number of price increases (4, while “B” still has 3) and is more likely to have the trend ++. At
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3 period 5 the Bayesian trader will close the position in “B” and will buy more shares of “A”. The investor
4 will repeat the same strategy in each and every next period.
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7 The optimal strategy thus involves selling winners rarely and selling losing stocks more often,
8 generating the opposite of the disposition effect. In particular, according to the sequence of prices in our
9 experiment design, the difference between PGR and PLR for a Bayesian investor is -0.84. An expected-
10 value trader will manifest high propensity to sell stocks at loss more quickly than stocks at gain. Across
11 our sample, we find that the measure of PGR and PLR are 0.36 and 0.34 respectively. This implies a
12 disposition effect value of 0.02, which, even if not significantly different from 0, is positive and
13 significantly greater than the benchmark expected value of -0.84 ($p < 0.001$).
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23 In particular, from Table 7, we show that, in contrast to the optimal trading strategy that a
24 Bayesian investor could follow, the subjects exhibit a tendency to buy the stock with the trend “0” and to
25 sell the stock with the trend “-“. These trading choices contrast with those of a Bayesian investor. For
26 example, whilst the optimal strategy involves to construct a portfolio picking the “++” stock, in our
27 sample subjects on average open positions with “0” stock.
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36 Figure 4 provides some additional insights to the distance between our sample’ selling behavior
37 and the one of the “optimal” expected value investor. The figure shows how our subjects’ preferences
38 deviate from optimality, in terms of selling trading decisions. Following an expected-value trading
39 strategy, on average the participant should realize gains on 2 occasions, demonstrating that almost 60% of
40 our sample’ decisions to monetize capital gains are suboptimal. Again, the design of the experiment,
41 based on short-term price momentum (Weber and Camerer 1998) encourages participants to keep stocks
42 that are performing well in their portfolio and not to hold a stock at loss. This justifies sub-optimality in
43 the 23% of subjects’ decisions to hold winning stocks and in more than 90% of participants’ decisions to
44 hold losers.
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50 51 **5. Results** 52

53 54 55 *5.1 Personality Traits and the Disposition Effect* 56 57 58 59 60

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3 From descriptive statistics and the correlations reported above, the heterogeneity in the elaboration of a
4 strategy to realize losses and gains seems to be driven by the effect of inter-individual differences on
5 various decision processes. To test this hypothesis and simultaneously control for the different factors
6 described in Section 4, we run the following model:
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$$DE = \alpha + \beta PT + \gamma X + \delta TF + \varepsilon \quad (2)$$

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11 where the level of disposition effect (DE) is defined as in Equation (1), PT is a vector of individual raw
12 scores for each of the five personality dimensions (*extraversion, conscientiousness, emotion stability,*
13 *agreeableness* and *openness to experience*), X is a vector of the different control variables (demographic,
14 country of origin, stock-market knowledge and trading experience) and TF is uninvested cash, i.e. the
15 budget that participants did not use during the simulation. Due to the censored nature of our dependent
16 variable, we use Tobit regression to estimate our model and results are reported in Table 8.
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29 In the baseline model (Column 1), consistent with Hypothesis 1, the coefficient of extraversion is
30 positive and highly significant suggesting that extroverts are more likely to express a disposition effect
31 than other individuals. Results also support Hypotheses 3 and 4. The traits of conscientiousness and
32 openness to experience are negatively correlated with the disposition effect, demonstrating that, the
33 behaviors based on a long-term goal achievement, low impulsivity and learning/explorative mechanisms
34 reduce the costly bias. However, we do not find any significant role played by the trait of emotion
35 stability, and especially of its sub-dimension anxiety, on the explanation of different levels of disposition
36 effect.
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42 The coefficient for the control variable “uninvested cash” is negative, confirming what was
43 reported in Dhar and Zhu (2006) where the “trading frequency helps investors become more willing to
44 sell losers, in turn reducing their DE”. Demographic characteristics, such as gender, country of origin,
45 education, stock-market knowledge and trading experience, have no statistically significant effect on
46 disposition effect, nor do the interaction variables between personality traits and the country dummy.
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50 Columns 2 to 6 show the output of a reduced model where each personality variable is included
51 without all the others. The results are similar to those in Column (1). In line with Mayfield et al. (2008),
52 who use the Big Five taxonomy to understand students’ preferences on short-term/long-term investment
53 intentions, we report a positive correlation between the trait of extraversion and the attitude to engage
54 (avoid) short-term (long-term) investments (Column 2). As for extraversion, Columns (3) and (4) confirm
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3 our propositions when just the traits of conscientiousness and openness to experience are respectively
4 included in the regression. Whereas psychology studies link the openness to experience to the intellectual
5 curiosity and intelligence (Harris, 2004), our results are in line with Grinblatt et al (2011), who document
6 a negative correlation between disposition effect and IQ measures.
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10 Our results hold both when we use alternative measures of DE, as in Dhar and Zhu (2006), and
11 when we employ different regression models (Probit and OLS).² For robustness, we also run the
12 regression in equation (2) for the Italian and Chinese sub-samples separately. Even if there is a drop in the
13 statistical significance (mainly due to the sample size reduction), in both the cohorts all personality traits
14 maintain the same direction in explaining the heterogeneity in disposition effect. Finally, as a potential
15 concern, one may argue that the correlation within personality traits and between personality and
16 demographics variables may produce multicollinearity problems and bias our findings. Specifically, Table
17 5 displays a modest correlation between extraversion and conscientiousness (0.16). To separate the
18 impact of these two variables and avoid multicollinearity issues, we substitute the variable extraversion
19 with the residuals of the regression between extraversion and conscientiousness. The new variable
20 therefore only captures the marginal explanatory power of the extraversion relative to what is already
21 explained by the variable conscientiousness. We use this approach for each significant inter-correlation
22 between our independent variables, but no significant changes are detected and our findings remain
23 consistent.
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34 *5.2 Personality Traits and the Proportion of Gains and Losses realized*

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36 To better analyze and test our predictions on the role of personality traits in altering individual investment
37 behavior we further disentangle the disposition effect focusing on the attitude to ride losers and winners
38 separately. Especially, we are interested in observing whether the role of personality traits differs in
39 explaining the financial decision-making in the domain of gains and losses. We therefore use the
40 Proportion of Gains realized (PGR) and the Proportion of Losses realized (PLR) as dependent variables
41 and run the same Tobit regression models specified in equation (2). Results are reported in Table 9.
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50 Consistent with our hypotheses, we find a specific pattern among the traits of extraversion,
51 conscientiousness and openness in influencing individual investment behavior. The coefficients in
52 Column 1 show that extraversion and conscientiousness have a role in increasing and decreasing the
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56 ²The authors define the DE as (RG/RL) (PG/PL), where RG and RL are the number of sales of winners and losers,
57 respectively and PG and PL are the number of paper gains and losses. This measure avoids the potential scaling bias
58 in the computation defined by Odean (1998).
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3 number of capital gains realized during the simulation. The coefficient of openness to experience is
4 negative, thus showing that open subjects are not in rush to sell winners. Our hypotheses are also
5 supported when looking at the coefficients reported in Column (2) that do not point to an attitude to close
6 rapidly losers for the traits of extraversion and conscientiousness but for openness to experience. In line
7 with our Hypothesis 4, we find indeed that those who **score high** on openness to experience keep winners
8 in their portfolio longer than losers. Columns (1) and (2) confirm what emerged from descriptive
9 statistics, i.e. that Chinese participants close more positive and negative positions than Italians. Finally,
10 the amount of not-invested cash positively relates with the PGR and PLR. In particular, from Column (1)
11 in selling a stock with a positive return the participant increases significantly the budget available to
12 operate in the market, while, from Column (2), when a subject closes negative positions the increase in
13 the not-invested cash is less strong.

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21 Other individual demographic characteristics, such as gender, education, stock-market knowledge
22 and trading experience are not associated with the tendency to ride losers and winners (we find a small
23 effect of gender only for the loss domain, $p < 0.1$). As for the previous analysis, interaction variables
24 between personality traits and the country dummy do not reveal any significant effect both on PLR and
25 PGR. The results hold also employing OLS and Probit models and taking into account each of the big five
26 personality traits individually. Our insights do not change also when we treat potential collinearity
27 problems from the correlations among the dependent variables using instrumental variables.

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33 These results show that DE may be driven by two distinct psychological processes, one related to
34 holding losers and the other to selling winners. We find that these two behavioral mechanisms are
35 uncorrelated and influenced by different personality traits. In particular, we show: 1) a greater sensitivity
36 of the rewarding system that motivate extroverts to quickly sell the stock at gain in order to receive a
37 burst of utility; 2) a tendency for conscientious subjects to suppress impulsivity not selling the security as
38 soon as it experiences an increase in the price while patiently waiting for higher cumulative returns; 3) an
39 ability for people who score high on openness to experience to work efficiently ascribing more value to
40 the new information that they can use to obtain better outcomes.

41 42 43 44 45 46 47 **6. Discussion and conclusions**

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50 Using personality inventory surveys as well as trading simulations, we model the role of personality traits
51 **to explain** the heterogeneity in DE among investors. We build on Realization Utility Theory and Big Five
52 Model to depict trading strategies that the subjects will adopt in line with their psychological
53 characterization.
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3 Although the existing literature demonstrates a wide tendency of investors to sell quickly stock at
4 gains rather than at losses, our results document that almost half of the sample does not show a positive
5 disposition effect. We investigate the drivers of this high variation in an individual psychological
6 perspective. At odds to the usual picture of successful investors who trade aggressively and impulsively,
7 we find that personality traits, like extraversion and conscientiousness, are respectively positively and
8 negatively related with the biased financial behavior. In line with Fenton-O’Creevey et al. (2004) and
9 Grinblatt et al. (2011) we find that less biased traders tend to be open to new experiences and less locked
10 into pre-conscious mechanisms that lead them to repeat the same action over time.

11
12 We document that personality traits influence the disposition effect by two distinct psychological
13 processes, one dealing with holding losers and the other with selling winners. In particular, extraverted
14 subjects have more chances than other individuals to ride losses instead of gains. Consistent with the
15 evidence of higher sensitivity to rewarding system, extroverts respond strongly to immediate rather than
16 postponed rewards. Subjects who score high on conscientiousness are instead less likely to be affected by
17 “hot” impulse to monetize capital gains as soon as they appear. In obtaining higher rewards, they alter
18 their emotional response and take the decisions that are more remunerative in the long term. These
19 findings also show the ability of people who score high on “openness to experience” to work efficiently
20 using new information to change trading strategies and obtain better payoffs. We also find that the same
21 trait influences individual investment behavior both for gains and for losses, leading subjects to keep
22 winners in their portfolio longer than losers.

23
24 Among the demographic variables taken into account in our paper, we found that trading
25 experience slightly moderates the role of personality traits in explaining the disposition effect level among
26 the subjects. The small size of the effect detected may be due to a lack of power due to limited number of
27 experienced investors in our sample. In a larger one or in one including also professionals’ traders, the
28 effect of trading experience in altering the correlation between personality and investment behavior may
29 become more pronounced. Moreover, employing an accurate analysis on traders’ real financial records
30 might offer a better control for some other possible drivers, such as taxes, transactions costs and
31 information asymmetry (Odean, 1998) excluded from our experimental setting. Even if we improved the
32 external validity of our sample with a specific experimental design, we believe that the relation between
33 personality traits and disposition effect begs for additional “real” data, particularly in light of Fenton-
34 O’Creevey et al.’s (2004) where the trading performances of investment bankers have been studied.

35
36 Our insights seem to suggest a specific “personality profile” less affected by the disposition effect
37 that is coherent, for example, with previous studies on conscientiousness and high income (Boyce and
38 Wood, 2011). The fact that personality traits explain part of the disposition effect variation among a
39 population suggests an implementation of the behavioral models that describe anomalies in asset pricing
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3 as naïve diversification and excessive trading. Especially, investigating whether the Five Factor Model
4 affects higher/lower number of trading operations and/or differences in the portfolio composition (e.g.
5 Brown and Taylor, 2014) offers insights for future analyses.
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8 Our experimental design leads us to question the relation between personality traits and
9 disposition effect over longer time horizon. We believe that, increasing the time frame in which analyze
10 the financial records, we could observe more complete individual investment strategies. For example, in
11 terms of trading frequencies (Dhar and Zhu, 2006; Kumar and Lim, 2008), we believe that a longer
12 horizon will give us the chance to report a pronounced relation between personality traits and disposition
13 effect, especially for the traits whose influence needs more stimuli to emerge (e.g. anxiety as in McCrae
14 and Costa, 1992). Again, considering the trading volume, a larger variation in the magnitude of the trades'
15 value could stimulate the sensitivity to reward differently, in turn affecting the timing of capital gains'
16 monetization. Finally, from the literature on disposition effect and types of securities exchanged (Kumar,
17 2009 and Chang et al., 2016), in a bigger trading window, we could observe how the personality traits
18 influence the disposition effect when stocks, mutual funds and bonds are taken into account separately.
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26 The specific interaction between personality traits and disposition effect deserves further
27 investigations in terms of external factors. For example, from McCrae and Costa (1992) it should be
28 interesting to test whether the introduction of a corporate news announcement or market events, moderate
29 the intensity of the relation between the Five Factor Model and the disposition bias. Again, the evidence
30 of individual psychological states **orientation** as a strategic outlook that people have in decision making
31 (Higgins, 1997) leads to speculate about the influence of retrieving information processes (implicit
32 memory, past experiences and context) in the relation between personality and individual financial
33 choices.
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39 Finally, our findings are also important for the investment firms and financial companies. On the
40 one hand, professional investors might be interested to leveraged on the different personality profile to
41 fine-tune their recruiting strategy. On the other hand, identifying a personality profile less influenced by
42 the disposition effect might motivate financial advisors to make investors aware of such bias and help
43 them to obtain better performances. Indeed, an investor who is informed about the consequences of the
44 disposition effect could be triggered to close fast the negative positions, deduct the losses in tax filing,
45 and increase the portfolio after-tax performance.
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REFERENCES

- Allport F. and Allport G. (1921) "Personality traits: their classification and measurement", *Journal of Abnormal and Social Psychology*, vol. 16;
- Almlund M., Duckworth A., Heckman J. and Kautz T. (2001) "Personality psychology and economics", *Handbook of the Economics of Education*;
- Aluja, A., Garcia, O. and Garcia L. (2003) "Relationship among extraversion, openness to experience, and sensation seeking", *Personality and Individual Differences*, vol. 35;
- Ball S. and Zuckerman M. (1990) "Sensation seeking, Eysenck's personality dimensions and reinforcement sensitivity in concept formation", *Personality and Individual Differences*, vol. 11;
- Barber B. M. and Odean T. (2001) "Boys Will Be Boys: Gender, Overconfidence, and Common Stock Investment", *Quarterly Journal of Economics*, vol. 116, n. 1;
- Barberis N. and Xiong W. (2009) "What Drives the Disposition Effect? An Analysis of a Long-Standing Preference-Based Explanation", *The Journal of Finance*, vol. 64, n. 2;
- Barberis N. and Xiong W. (2012) "Realization utility", *The Journal of Financial Economics*, vol. 104;
- Barrick M., Mount M. and Li N. (2002) "The Theory of Purposeful Work Behaviour: The Role of Personality, Job Characteristics, and Experienced Meaningfulness", *Academy of Management Journal*, vol. 38;
- Bassi A., Colacito R. and Fulghieri P (2013) "'O Sole Mio: An Experimental Analysis of Weather and Risk Attitudes in Financial Decisions", *The Review of Financial Studies*, vol. 26;
- Bello D., Leung K., Radebaugh L., Tung L. and van Witteloostuijn A. (2009) "From the editors: Student samples in international business research.", *Journal of International Business Studies*, vol. 40;
- Ben-David I. and Hirshleifer D. (2012) "Are investors really reluctant to realize their losses? Trading responses to past returns and the disposition effect", *The Review of Financial Studies*, vol. 5, n.8;
- Birru J. (2015) "Confusion of Confusions: A Test of the Disposition Effect and Momentum", *Review of Financial Studies*, vol. 28;
- Boyce C. and Wood A. (2011) "Personality and the marginal utility of income: personality interacts with increases in household income to determine life satisfaction", *Journal of Economic Behavior and Organization*, vol. 78;
- Boyle G. J. (2008) "Critique of the five-factor model of personality", *The SAGE handbook of personality theory and assessment, Vol 1: Personality theories and models*;
- Brown S. and Taylor K. (2014) "Household Finances and the 'Big Five' Personality Traits", *Journal of Economic Psychology*, vol. 45;

1
2
3 Burks S., Lewis C., Kivi P., Wiener A., Anderson J., Gotte L., De Young C. and Rustichini A. (2015)
4 “Cognitive skills, personality and economic preferences in collegiate success”, *Journal of Economic*
5 *Behavior and Organization*, vol. 115;

6
7
8 Camerer C. (2008) “The Case for Mindful Economics”, in *Foundations of Positive and Normative*
9 *Economics*. New York: Oxford University Press;

10
11 Chang T., Solomon D. and Westerfield M. (2014) “Looking for someone to blame: delegation,
12 cognitive dissonance, and the disposition effect”, *forthcoming on Journal of Finance*;

13
14 Chui P. (2010) “An Experimental Study of the Disposition Effect: Evidence From Macau”, *Journal of*
15 *Psychology and Financial Markets*, vol. 2, n.4;

16
17
18 Conlin A., Kyröläinen P., Kaakinen M., Järvelin M., Perttunen J. and Svento R. (2015) “Personality
19 traits and stock-market participation”, *Journal of Empirical Finance*, vol. 33;

20
21
22 Costa P. and McCrae R. (1992) “NEO PI-R professional manual”, *Odessa, FL: Psychological*
23 *Assessment Resources, Inc.*;

24
25
26 Da Costa Jr. N., Goulart M., Cupertino C., Maced Jr. J. and Da Silva S. (2013) “The disposition effect
27 and investor experience”, *Journal of Banking and Finance*, n. 37;

28
29
30 Daly M., Harmon C. and Delaney L. (2009) “Psychological and biological foundations of time
31 preference”, *Journal of the European Economic Association*, vol. 7;

32
33
34 Depue R. and Collins P. (1999) “Neurobiology of the structure of personality: dopamine, facilitation
35 of incentive motivation, and extraversion”, *Behavioural and Brain Sciences*, vol. 22, n. 3;

36
37
38 Dhar R. and Zhu N. (2006) “Up close and personal: investor sophistication and the disposition effect”,
39 *Management Science*, vol. 52, n. 5;

40
41
42 Durand R. B., Newby R., Peggs L and Siekierka M. (2013) “Personality”, *Journal of Behavioral*
43 *Finance*, vol. 14;

44
45
46 Eysenck H.J. (1967) “Biological dimensions of personality”, *Handbook of personality: theory and*
47 *Research*, New York: Guilford;

48
49
50 Fellner G. and Maciejovsky B. (2002) "Risk Attitude and Market Behaviour: Evidence from
51 Experimental Asset Markets”, *Strategic Interaction*, vol. 34;

52
53
54 Feingold A. (1994) “Gender differences in personality”, *Psychological Bulletin*, vol. 116;

55
56
57 Fenton-O’Creevey M., Nicholson N., Soane E. and Willman P. (2004) “Traders: Risks, decisions, and
58 management in financial markets”, *UK: Oxford University Press*.

59
60
61 Fleeson W. (2001) “Toward a structure-and process-integrated view of personality: traits as density
62 distributions of states”, *Journal of Personality and Social Psychology*, vol. 80, n. 6;

63
64
65 Fletcher J. (2013) “The effects of personality traits on adult labor market outcomes: Evidence from
66 sibilings”, *Journal of Economic Behavior and Organization*, vol. 89;

- 1
2
3 Frazzini A. (2006) “The disposition effect and underreaction to news”, *Journal of Finance*, vol. 111, n.
4
5 4;
- 6 French K. and Poterba J. (1991) “Investor diversification and international equity markets”, *American*
7
8 *Economic Review*, vol. 81, n. 2;
- 9
10 Frydman C., Barberis N., Camerer C., Bossaerts P and Rangel A. (2014) “Using neural data to test a
11
12 theory of investor behaviour: an application to realization utility”, *Journal of Finance*, vol. 69, n.2;
- 13 Frydman C. and Rangel A. (2014) “Debiasing the disposition effect by reducing the saliency of
14
15 information about a stock’s purchase price”, *Journal of Economic Behavior and Organization*, vol. 107;
- 16 Goetzmann W. N. and Massa M. (2008) “Disposition Matters: Volume, Volatility, and Price Impact of
17
18 a Behavioural Bias”, *Journal of Portfolio Management*, vol. 34, n. 2;
- 19 Goldberg L. (1992) “The development of markers for the Big-Five factor structure”, *Psychological*
20
21 *Assessment*, 26;
- 22
23 Goldberg L. (1999) “A Broad-Bandwidth, Public-Domain, Personality Inventory Measuring the
24
25 Lower-Level Facets of Several Five-Factor Models”, *Personality Psychology in Europe*, vol. 7;
- 26 Grinblatt M. and Han B. (2005) “Prospect theory, mental accounting and momentum”, *Journal of*
27
28 *Financial Economics*, vol. 78;
- 29 Grinblatt M. and Keloharju M. (2000) “The Investment Behaviour and Performance of Various
30
31 Investor Types: A Study of Finland’s Unique Data Set”, *Journal of Financial Economics*, vol. 55;
- 32 Grinblatt M. and Keloharju M. (2001) “How Distance, Language and Culture Influence Stockholdings
33
34 and Trade”, *The Journal of Finance*, vol. 56;
- 35 Grinblatt M., Keloharju M. and Linnainmaa J. (2011) “IQ, Trading Behaviour, and Performance”,
36
37 *Journal of Financial Economics*, vol. 102;
- 38
39 Harris J. (2004) “Measured intelligence, achievement, openness to experience, and creativity”,
40
41 *Personality and Individual Differences*, vol. 36, n. 4;
- 42 Hartzmar S. (2014) “The worst, the best, ignoring all the rest: the rank effect and trading behaviour”,
43
44 *Review of Financial studies*, forthcoming;
- 45 Higgins T. (1997) “Beyond Pleasure and Pain”, *American Psychologies*;
- 46 Hsee C. K. and Weber U.E. (1999) “Cross-National Differences in Risk Preferences and Lay
47
48 Predictions”, *Journal of Behavioural Decision Making*, vol. 12, n. 2;
- 49 Huberman G. (2001) “Familiarity breeds investment ”, *Review of Financial Studies*, vol. 14, n. 3;
- 50 John O. and Srivastava S. (1999) “The Big-Five trait taxonomy: History, measurement, and theoretical
51
52 perspectives” in L. A. Pervin and O. P. John (Eds.), *Handbook of personality: Theory and research*, vol.
53
54 2, New York: Guilford Press;
- 55
56
57
58
59
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1
2
3 Kahneman D. and Tversky A. (1979) "Prospect Theory: An Analysis of Decision under Risk",
4 *Econometrica*, vol. 47, n. 2;

5
6 Kassir S. (2003) "Psychology", *Prentice-Hall fourth edition*;

7
8 Knetsch J. and Sniden J. (1984) "Willingness to pay and compensation demanded: experimental
9 evidence of an unexpected disparity in measures of value", *Quarterly Journal of Economics*, vol. 55;

10
11 Kuhnen C. and Knutson B. (2005) "The neural basis of financial risk taking", *Neuron*, n. 47;

12
13 Larsen R. and Ketelaar T. (1989) "Extraversion, neuroticism and susceptibility to positive and
14 negative mood induction procedures", *Personality and Individual Differences*, vol. 10;

15
16 Lauriola M and Levin I. (2001) "Personality traits and risky decision-making in a controlled
17 experimental task: an explanatory study", *Personality and Individual Differences*, vol. 31;

18
19 Le Pine J., Colquitt J. and Erez A. (2000) "Adaptability to changing task contexts: effects of general
20 cognitive ability, conscientiousness, and openness to experience", *Personnel Psychology*, vol. 53;

21
22 Martin L and Potts G (2004) "Reward sensitivity in impulsivity", *Neuroreport*, vol. 15, n. 9;

23
24 Mayfield C., Perdue G. and Wooten K. (2008) "Investment management and personality type",
25 *Journal of Financial Services Review*, vol. 17;

26
27 McAdams and Donnellan (2009), "Facets of personality and drinking in first-year college students",
28 *Personality and Individual Differences*, vol. 46;

29
30 McCrae R. and Costa P. (1987) "Validation of the five-factor model of personality across instruments
31 and observers", *Journal of Personality and Social Psychology*, n. 52;

32
33 McCrae R. and Costa P. (1996) "Toward a new generation of personality theories: Theoretical
34 contexts for the five-factor model", In J. S. Wiggins (Ed.), *The five-factor model of personality:
35 Theoretical perspectives (pp. 51-87)*. New York: Guilford;

36
37 Mishra S. and Lalumière M.L. (2011) "Individual differences in risk-propensity: Associations between
38 personality and behavioural measures of risk", *Personality and individual differences*, n. 50;

39
40 Nicholson N., Soane E., Fenton-O'Creevy and Willman P. (2005) "Personality and domain-specific
41 risk taking", *Journal of Risk Research*, vol. 8, n. 2;

42
43 Odean T. (1998) "Are Investors Reluctant to Realize Their Losses?", *Journal of Finance*, vol. 53, n. 5;

44
45 Odean T. (1999) "Do Investors trade too much?", *The American Economic Review*, vol. 89, n. 5;

46
47 Ozer D. and Benet-Martinez V. (2006) "Personality and prediction of consequential outcomes",
48 *American Review of Psychology*, vol. 57;

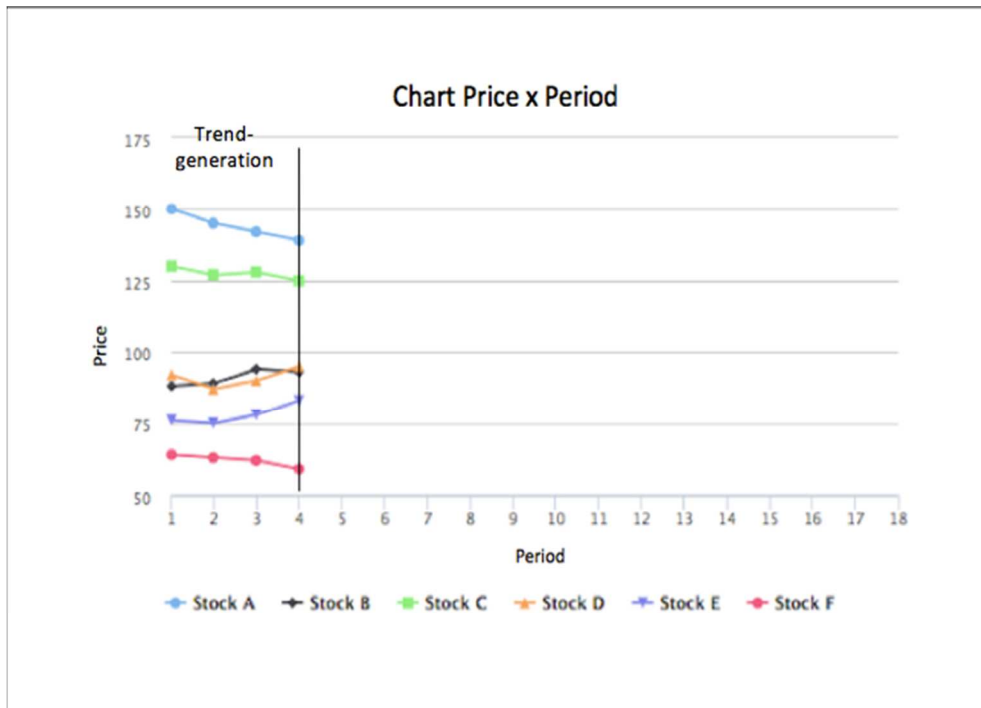
49
50 Peterson R. and Merunka D. (2014) "Convenience samples of college students and research
51 reproducibility", *Journal of Business Research*, vol. 67;

52
53 Rolfhus E. and Ackerman P. (1999) "Assessing individual differences in knowledge: Knowledge
54 structure and traits", *Journal of Education Psychology*, vol. 91;

- 1
2
3 Saucier G. (2002) "Orthogonal markers for orthogonal factors: The case of the Big Five", *Journal of*
4 *Research in Personality*, vol. 36;
5
6 Schacter D., Gilbert D. and Wegner D. (2011) "Psychology (2nd Edition)", *New York: Worth*;
7
8 Shefrin H. and Statman M. (1985) "The disposition to sell winners too early and ride losers too long:
9 theory and evidence", *The Journal of Finance*, vol.40, n. 3;
10
11 Smillie L. (2013) "Why does it feel good to act like an extravert?", *Social and Personality Psychology*
12 *Compass*, vol. 7, n.12;
13
14 Statman M. (2008) "Countries and culture in behavioural finance", *Institute Conference Proceedings*
15 *Quarterly*;
16
17 Torrubia R., Avila C., Molto J. and Caseras X. (2001) "The Sensitivity to Punishment and Sensitivity
18 to Reward Questionnaire as a measure of Grayos anxiety and impulsivity dimensions", *Personality and*
19 *Individual Differences*, vol. 31;
20
21 Triandis H.C. (2001) "Individualism-Collectivism and Personality", *Journal of Personality*, vol. 69;
22
23 Tupes E. and Christal R. (1961) "Recurrent personality factors based on trait ratings", *Technical*
24 *Report, USAF, Lackland Air Force Base, TX*;
25
26 Tversky A. and Kahneman D. (1981) "The framing of decisions and the psychology of choice",
27 *Science*, vol. 211, n. 4481;
28
29 Van der Linden D., Nijenhuis J. and Bakker A. (2010) "The general factor of personality: A meta-
30 analysis of Big Five intercorrelations and a criterion-related validity study", *Journal of Research in*
31 *Personality*, vol. 44.
32
33 Weber M. and Camerer C. (1998) "The disposition effect in securities trading: an experimental
34 analysis", *Journal of Economic Behaviour and Organization*, vol. 33;
35
36 Zuckerman M. (1969) "Theoretical formulations", *Appleton-Century-Crofts*.
37
38 Zuckerman M. (1991) "Psychobiology of personality", *New York: Cambridge University Press*;
39
40 Zuckerman M., Joireman J., Kraft M. and Kuhlman D. (1999) "Where do motivational and mood traits
41 fit within three factor models of personality", *Personality and Individual Differences*, n. 26;
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Figure 1
Chart price/period

Figure 1 shows the visual outcome of the price path generated by the simulation software. The whole period is divided into 18 sub-periods, 4 of which are not generated for trading purpose but only for allowing the participants to estimate the likelihood of future stock price increase.

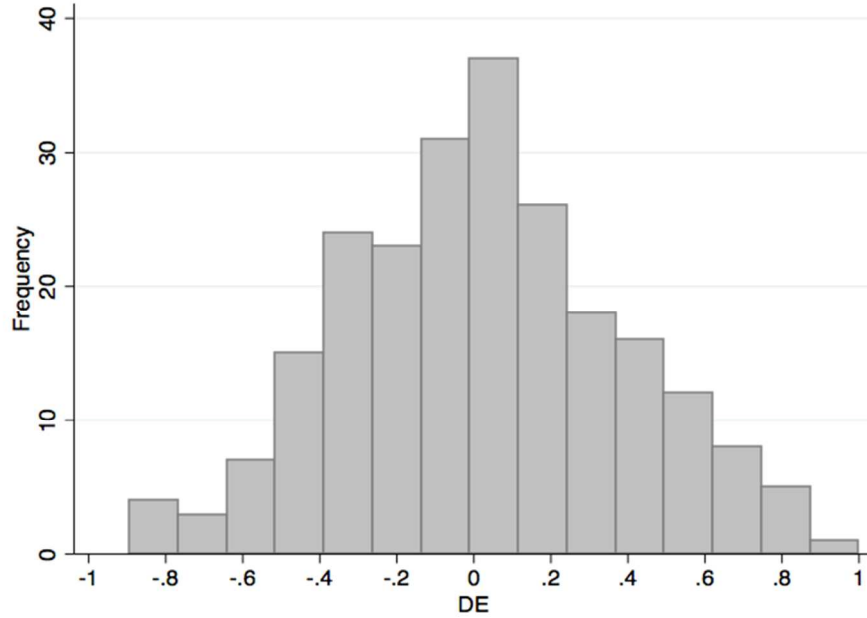


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Figure 2

Distribution of Disposition Effect (DE) across the sample.

The figure shows the distribution of the disposition effect levels across the participants. On the x-axis there is the disposition effect level while on y-axis there is the distribution frequency.

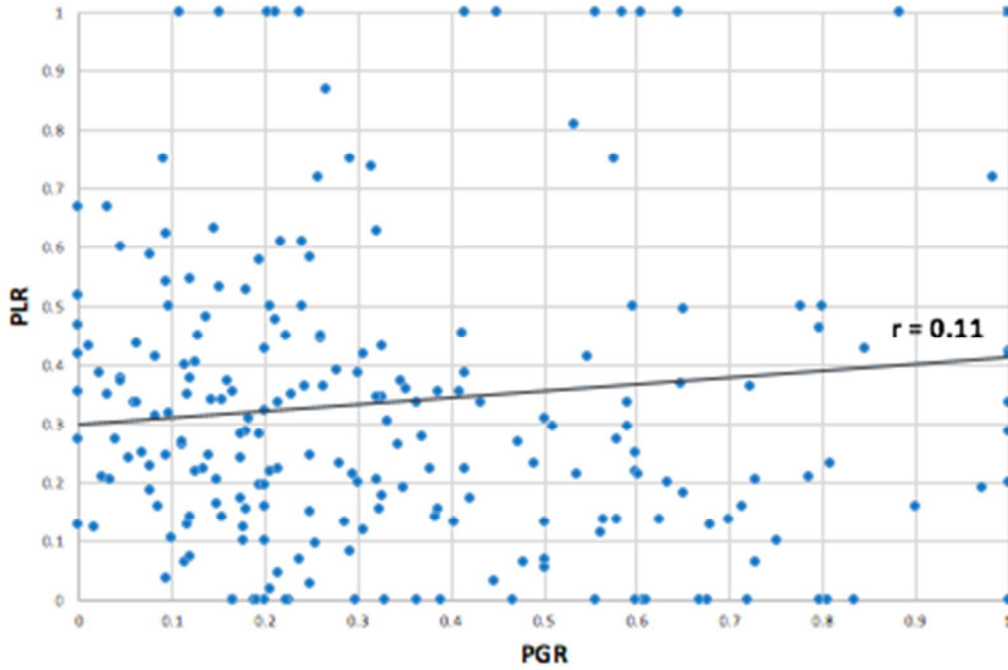


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Figure 3

Correlation between PGR and PLR.

The scatter plot relates the PGR (x-axis) to the PLR (y-axis). Each point represents a single participant.

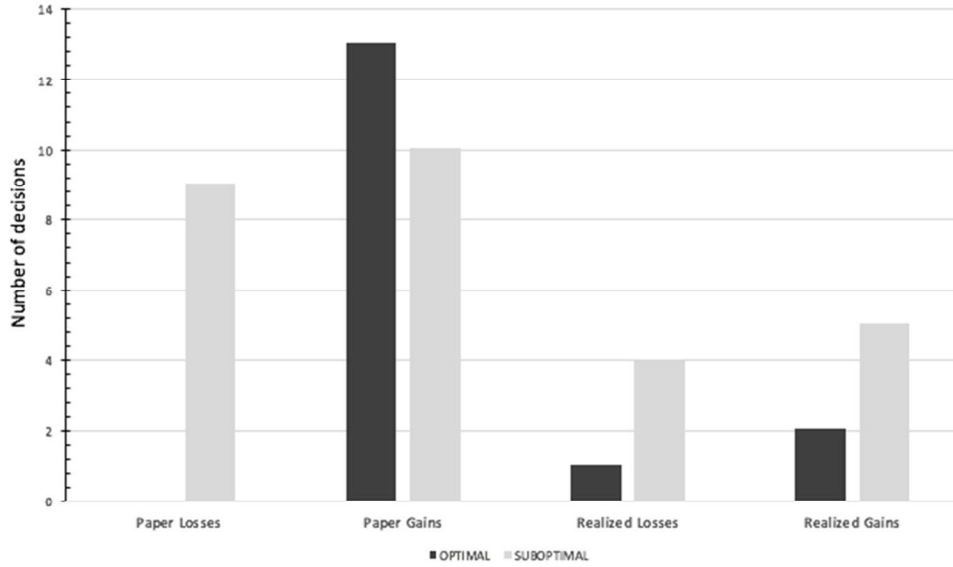


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Figure 4

Number of sell decisions: optimality and sub-optimality.

Figure 4 illustrates the number of sell decisions by type (realized gains, realized losses, paper gains, paper losses). The optimal number of decisions is based on a Bayesian strategy that involves buying the stock that has exhibited in the previous periods the larger number of price increases and selling all the other stocks; the suboptimal decision is any other choice different from the optimal.



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Table 1 Big Five Personality Traits

This table presents all the facets within each of the five personality traits of the Five Factor Model. The list of adjectives are from McCrae and Costa (1996) and from John and Srivastava (1999)

Five Personality Traits	Constituent Traits (adjectives)
Extraversion (Introversion)	Outgoing, energetic, sociable, friendly, talkative, assertive, enthusiastic, gregarious.
Conscientiousness (Careless)	Efficient, organized, prepared, dependable, self-disciplined, not careless, respectful of duties.
Openness to Experience (Cautiousness)	Inventive, curious, unconventional, excitable.
Neuroticism (Emotion Stability)	Anxious, irritable, shy, moody, not self-confident, depressed, tense, stressed out.
Agreeableness (Antagonism)	Modest, not demanding, warm, altruistic, generous, not stubborn, likeable, enjoyable.

Table 2 Hypotheses relationship between personality traits and disposition effect

This table reports, for each of the five personality trait, the main characterizations, the expected behavior and the hypothesis relative to their effect on the level of disposition effect.

Personality Trait	Extraversion	Conscientiousness	Openness	Emotion Stability	Agreeableness
Domain	Rewarding System	Impulsivity system	Willingness to novelty	Punishment System	
Effect	Immediate rewards over delayed rewards	Suppress impulsivity working for goals that are not immediate	Sensitivity to new information & less harm avoidance behavior	Weaker respond to negative signals	Plays a weak role in decision-making under uncertainty
Expected behavior	Monetize capital gains as soon as they appears.	Waiting in selling stocks at gain	Closing quickly negative positions	Closing faster negative positions	
Expected DE sign	+	-	-	-	
Expected side	Higher number of gains realized	Lower number of gains realized	Higher number of losses realized	Higher number of losses realized	

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Table 3 Stock-price evolution mechanism

The Table describes the mechanism behind the price updates of each type of stocks.

Type of stock	Probability of a price increase	Probability of a price decrease
--	35%	65%
-	45%	55%
0	50%	50%
+	55%	45%
++	65%	35%

Table 4 Summary Statistics - Socio-demographic and Personality

The Table reports descriptive statistics on demographics and personality traits variables for the entire sample.

	Obs	Mean	Median	St. Dev.	Min.	Max.
Demographics						
Age	229	22.48	22.00	1.95	19.00	31.00
Education	230	1.54	2.00	0.55	1.00	3.00
Stock-Market Knowledge	230	1.50	1.00	0.54	1.00	3.00
Trading Experience	230	1.32	1.00	0.84	1.00	5.00
Personality traits						
Extraversion	230	33.57	34.20	5.50	18.00	47.500
Conscientiousness	230	38.25	38.70	5.43	20.00	50.00
Openness	230	37.21	37.50	5.41	24.00	49.20
Emotion Stability	230	31.14	30.80	7.22	13.00	48.30
Agreeableness	230	35.38	35.80	5.37	17.50	48.20

Age is the age of the participant. Education is a categorical variable taking the following values if the participant: 1 is undergraduate; 2 is graduate; 3 is a post-graduate student. Stock market knowledge is a variable taking values of 1 whether participant has not knowledge on financial markets, 2 if he has a background education in finance or related areas and 3 if he works/worked for stock-market services. Finally, trading experience takes the following values of: 1 if the participant has never invested; 2 if he invested just one time; 3 whether she/he invested for maximum one year; 4 for maximum three years; 5 if he invested for more than three years.

Table 5 Correlations: The Big-Five

This table contains the pairwise Pearson correlations among the Big Five trait values and the pairwise Pearson correlation among the demographics variable and between the Big Five traits and the demographics variables.

Personality Traits					
	Extraversion	Conscientiousness	Openness	Emotion stability	Agreeableness
Extraversion	1.000				
Conscientiousness	0.157*	1.000			
Openness	0.341**	0.355**	1.000		
Emotion Stability	-0.034	0.140*	0.067	1.000	
Agreeableness	-0.127	0.414**	0.075	0.236**	1.000

Personality and Demographics					
	Extraversion	Conscientiousness	Openness	Emotion Stability	Agreeableness
Gender	0.175**	-0.046	0.184**	0.224**	-0.104
Education	0.102	0.211**	0.092	0.103	0.053
Knowledge	-0.140*	-0.084	-0.072	-0.131*	-0.091
Trading Exp.	0.040	0.039	0.169**	0.020	-0.004

Demographics				
	Gender	Education	Knowledge	Trading Exp.
Gender	1.000			
Education	0.013	1.000		
Knowledge	-0.106	-0.165*	1.000	
Trading Exp.	0.072	0.068	0.142*	1.000

* p<0.05 and ** p <0.01

Table 6 Summary Statistics - Trading Records 1/2

The table reports descriptive statistics of the level of the disposition effect (DE) along with the two components: the ratio of the number of stocks sold over those sold and not sold for both gain and losses (PGR = Proportion of gains realized = Realized Gains/ Realized Gains + Paper Gains; PLR = Proportion of losses realized = Realized Losses/ Realized Losses + Paper Losses). The table likewise displays the statistics for the control variables: *realized gains* is the number of stocks sold at gain, *realized losses* is the number of stocks sold at loss, *paper gains/losses* is the number of stocks hold at gain/loss but not sold. *Number of operations* is the total number of stocks traded by the participant during the simulation, while *number of operations – buy(sell)* refers to the number of stocks bought (sold) by the participant during the simulation. *Return from winner selling* describes the return that participant obtain when he sells stocks at gain, in contrast *loss from loser selling* is the loss the subject experiences when he sells stocks at price lower than the purchase price. *Uninvested cash* reflects the available budget that the participant does not use during the simulation.

	Obs	Mean	Median	Std.	Minimum	Maximum
	Deviation					
	Disposition Effect					
Paper Gains	230	50.37	37.50	42.97	0.00	194.00
Paper Losses	230	39.54	31.00	35.01	0.00	181.00
Realized Gains	230	23.33	17.00	24.16	0.00	162.00
Realized Losses	230	15.41	12.00	13.43	0.00	70.00
PGR	230	0.36	0.27	0.27	0.00	1.00
PLR	230	0.34	0.28	0.27	0.00	1.00
DE	230	0.02	0.00	0.36	-0.89	1.00
	Trading Records					
Number of operations	230	15.94	15.00	8.39	3.00	54.00
Number of operations	230	10.32	9.00	6.65	1.00	43.00
Number of operations	230	26.26	24.00	14.48	5.00	97.00
Return from winner	230	0.03	0.02	0.02	0.00	0.18
Loss from loser selling	230	-0.02	-0.02	0.02	-0.16	0.00
Uninvested cash	230	576.51	505.42	464.87	0.00	3711.71
	Disposition Effect and trading frequency					
	(a) DE		(b) DE		(a-b) Difference	
Number of operations	10 TH Percentile = 0.055		90 TH Percentile = -0.040		0.095 (p<0.182)	
Uninvested cash	10 TH Percentile = 0.032		90 TH Percentile = 0.167		-0.135 (p<0.132)	

Table 7 Summary statistics - Trading Records 2/2

This table presents trading descriptive statistics broken down by the type of stock and the number of subjects divided for type of stock sold and purchased. There are 6 stocks with 5 types of stock-trend: stock 1 or C (-) with a likelihood to experience a rising in price about 35 per cent; stocks B and D or 2 and 3 (-) of 45 per cent; stock A or 4 (0) about 50 per cent; stock E or 5 (+) 55 per cent and of 65 per cent for stock F or 6 (++)). During the simulation subjects trade with 6 stocks with two stocks of the same type (-) (B and D or 2 and 3).

	Obs	Mean	Median	Std. Deviation	Minimum	Maximum
Type of stock						
Type of stock - sell	198	3.62	3.00	1.65	1.00	6.00
Type of stock - buy	206	3.83	4.00	1.63	1.00	6.00
Stock trend						
Stocks	(1) C	(2) B	(3) D	(4) A	(5) E	(6) F
Trend	--	-	-	0	+	++
# of subjects selling mainly this stock	33	52	34	15	21	43
# of subjects buying mainly this stock	31	44	38	14	32	47

Table 8 Regression Table: Disposition Effect

This table contains a set of Tobit regressions in explaining the tendency to ride losers instead of gains for the entire sample. The dependent variable is the disposition effect as measured by Odean (1998), $DE = PGR - PLR$. The independent variables include the personality traits (extraversion, conscientiousness, emotion stability, agreeableness and openness), demographics data (gender, country origin, education, stock-market knowledge and trading experience) and a variable for the trading frequency (capital not-invested). The dummy gender takes value of 0 if female, 1 if male. The dummy country takes value of 0 if the participant is Chinese and 1 if Italian).

	1	2	3	4	5	6
	Disposition Effect	Disposition Effect	Disposition Effect	Disposition Effect	Disposition Effect	Disposition Effect
Constant	0.073 (0.27)	-0.406** (-2.19)	0.356* (1.82)	0.369* (1.89)	-0.097 (-0.60)	0.028 (0.13)
Extraversion	0.017*** (3.55)	0.011** (2.36)				
Conscientiousness	-0.013** (-2.48)		-0.012*** (-2.74)			
Openness	-0.014*** (-2.80)			-0.014*** (-2.83)		
Emotion Stability	0.002 (0.65)				0.001 (0.24)	
Agreeableness	0.005 (0.92)					-0.003 (-0.55)
Gender	-0.009 (-0.18)	0.003 (0.06)	0.003 (0.06)	0.018 (0.35)	0.008 (0.16)	0.011 (0.21)
Dummy Country	-0.005 (-0.07)	-0.073 (-1.14)	-0.015 (-0.25)	0.044 (0.68)	-0.019 (-0.31)	-0.030 (-0.48)
Education	0.044 (1.02)	0.031 (0.70)	0.051 (1.14)	0.028 (0.64)	0.028 (0.62)	0.032 (0.71)
Knowledge	0.038 (0.86)	0.033 (0.73)	0.018 (0.40)	0.0193 (0.42)	0.024 (0.53)	0.020 (0.44)
Trad. Experience	-0.009 (-0.33)	-0.029 (-1.00)	-0.020 (-0.70)	-0.007 (-0.25)	-0.024 (-0.84)	-0.024 (-0.83)
Uninvested cash	0.194* (1.87)	0.163 (1.55)	0.230 (2.17)	0.187 (1.79)	0.188 (1.76)	0.192 (1.80)
N	230	230	230	230	230	230
R2	0.153	0.053	0.063	0.065	0.024	0.026

t -statistics in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 9 Regression Table: PGR and PLR

The Table reports two Tobit regressions where the dependent variables are the proportion of gains (Column 1) and losses (Column 2) realized as measured by Odean (1998), $PGR = RG/(PG+RG)$ and $PLR = RL/(PL+RL)$. In both models the independent variables include the personality traits (extraversion, conscientiousness, emotion stability, agreeableness and openness), demographics data (gender, country origin, education, stock-market knowledge and trading experience) and a variable for the trading frequency (capital not-invested). The dummy gender takes value of 0 if female, 1 if male. The dummy country takes value of 0 if the participant is Chinese and 1 if Italian.)

	1	2
	PGR	PLR
Constant	0.361* (1.85)	0.288 (1.41)
Extraversion	0.015*** (4.61)	-0.001 (-0.36)
Conscientiousness	-0.009** (-2.46)	0.004 (0.98)
Openness	-0.006* (-1.75)	0.008** (2.09)
Emotion Stability	0.003 (1.07)	0.001 (0.15)
Agreeableness	0.001 (0.10)	-0.004 (-1.14)
Gender	0.054 (1.48)	0.063* (1.66)
Dummy Country	-0.232*** (-4.85)	-0.227*** (-4.54)
Education	-0.006 (-0.19)	-0.050 (-1.54)
Stock Market Know.	0.034 (1.06)	-0.004 (-0.14)
Trading Experience	-0.016 (-0.77)	-0.006 (-0.29)
Uninvested cash	0.280*** (3.78)	0.084 (1.10)
N	230	230
R2	0.944	0.542

t-statistics in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.