TRADER PERSONALITY AND TRADING PERFORMANCE

An explorative financial market pilot experiment

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ABSTRACT

Behavioral finance is a booming discipline. To date, the main source of inspiration for behavioral finance scholars has been cognitive psychology. Cognitive psychology offers a rich set of insights as to human decision-making, and the biases that tend to influence human decision-making processes. Such biases provide important reasons as to why anomalies may characterize financial market behavior. In this explorative study, we build on this insightful tradition by merging in insights from yet another psychology sub-discipline: personality psychology. Learning from decades of research in management sciences, we argue that a human being's personality is a key determinant of her or his behavior and performance. We illustrate, for a limited sub-set of six personality traits (i.e., locus of control, maximizing tendency, regret susceptibility, self-monitoring, sensation seeking and type-A/B behavior), how a similar logic can be applied in the context of the study of trader behavior and performance. We explore our line of reasoning in a pilot financial market experiment, involving 34 economics students. The preliminary results are promising.

1. INTRODUCTION

In the management domain, studies into the relationship between individual human features and organizational outcomes abound. In the current exploratory pilot study, we suggest to apply ideas from this behavioral management literature to issues in behavioral finance. In so doing, another branch will be added to the already flourishing tree of behavioral finance (see Barberis, Shleifer and Vishny, 1998, and, for an opposite view, Fama, 1998), as the key argument here is that financial market 'anomalies' can be explained by merging in insights from psychology-inspired literatures. Starting point in behavioral management is the assumption that what happens in and to an organization can – at least in part – be explained with reference to key features of the *homo sapiens* who together keep the organization going. Ignoring the large micro-micro literature in organizational behavior, which deals with individual-level research in such areas as employee motivation and employer leadership (Robbins, 2002), we focus here on that part of behavioral management that ultimately seeks to improve the extant explanation of differences in organizational performance by introducing behavioral insights into the theory of the firm (van Witteloostuijn, 1998, 2002 & 2003; Jansen, van Lier and van Witteloostuijn, 2007). That is, the leading question is: Why do some organizations perform (so much) better than others?

To date, the main source of inspiration for behavioral finance scholars has been cognitive psychology. Cognitive psychology offers a rich set of insights as to human decision-making, and the biases that tend to influence human decision-making processes. Such biases provide important reasons as to why anomalies may characterize financial market behavior. By now, the number of studies in this "cognitive finance" tradition is huge. In the current explorative study, we build on this insightful tradition by merging in insights from yet another psychology sub-discipline: personality psychology. Learning from decades of research in behavioral management sciences, we argue that a human

being's personality is a key determinant of her or his behavior and performance. We illustrate, for a limited sub-set of six personality traits, how a similar logic can be applied in the context of the study of trader behavior and performance. Subsequently, we explore our line of reasoning in a pilot financial market experiment. Of course, our empirical study cannot be but exploratory. Therefore, we speculate rather extensively about promising future work in an appraisal.

Indeed, a limited number of studies already explored the personality psychology – behavioral finance interface. Here, we would like to briefly reflect on the four examples we were able to find. First, McInish (1980, 1982), in two early studies of individual investors, linked riskiness of investment opportunities to risk attitude, and further to the locus-of-control personality trait. This trait captures the degree to which individuals feel that they are in control of their own life and have the capacity to influence their environment (Rotter, 1966). Individuals with a strong control belief are referred to as internals, and their counterparts as externals. So, external individuals perceive themselves as helpless and as lacking the power to determine their own fates. Based on a student sample, McInish (1980) concluded that persons with an external locus of control favor less risky portfolios. In a study of actual investors, though, McInish (1982) found that externals tended to choose more risky portfolios.

Second, building on these ideas, Chui (2001) experimentally examined the disposition effect – the tendency to sell winning assets too soon and hold losing assets transactions for too long – and, additionally, explored the influence of locus of control as a personality trait. He found a negative relationship between locus of control and disposition effect – that is, external individuals appear to be less affected by the disposition effect. However, locus of control does not seem to impact on trading volume as such.

Third, combining insights from cognitive and personality psychology, Biais, Hilton, Mazurier and Pouget (2005) considered the influence of overconfidence in judgment and of self-monitoring as a personality trait as two human features that might relate to trading performance in an experimental asset market. High self-monitors possess greater social sensitivity than low self-monitors, and low self-monitors are less aware of others' reactions – or, at least, are less concerned with them (Snyder, 1987). Particularly relevant in the current paper's context is that they found support for their hypothesis that high self-monitors achieve superior trading performance, possibly due to strategic behavior. However, this effect turned out to be significant only for the male individuals in their sample, and non-significant for females.

Fourth, Fenton-O'Creevy, Nicholson, Soane and Willman (2005) studied the influence of illusion of control, a cognitive bias to which in particular individuals with a high internal locus-of-control personality are susceptive, as well as the Big Five (Costa and McCrae, 1992a, 1992b) on total remuneration. The Big Five (neuroticism, extraversion, openness, agreeableness and conscientiousness) represent a comprehensive set of factors designed to captured a wide spectrum of personality traits, each consisting of several lower-level traits such as anxiety, modesty or self-discipline (for an overview, see Matthews, Deary and Whiteman, 2003). The investigation into this relationship was part of an extensive study of 118 traders and trader managers in four large London investment banks between 1997 and 2002. Based on a sub-sample of 64 traders, they found a significant negative effect of illusion of control and certain personality traits, such as neurotism and emotionality, as well as a positive significant effect of openness to experience.

We offer a three-fold contribution to this emerging, but still very limited, "personality finance" literature. First, we develop a general framework for this type of study, translating behavioral management logic to a behavioral finance context. Second,

we illustrate the general logic for six personality traits that can be expected to be relevant: locus of control, maximizing tendency, regret susceptibility, self-monitoring, sensation seeking and type-A/B behavior. Third, we explore our argument in a pilot financial market experiment with 34 economics students. The paper is structured as follows. In Section 2, we present our general framework. Subsequently, in Section 3, we introduce the six personality traits that we focus on in our empirical study. Next, in Section 4, we explain our experimental design. After that, in Section 5, we present preliminary evidence. Finally, in Section 6, we offer an appraisal.

2. GENERAL FRAMEWORK

Without any pretension of completeness, we briefly introduce two important vehavioral management theories that seek for an answer to our central question as to human personality – behavior – performance linkages: corporate demography and upper echelon theories (Boone, De Brabander, van Olffen and van Witteloostuijn, 2004; Boone, van Olffen and van Witteloostuijn, 2005). In a way, both theories open up the black box of the firm by making explicit the human dimension that co-determines organizational behavior and performance, adding the latter to well-established theories of external and internal performance drivers (Boone, Carroll and van Witteloostuijn, 2002 & 2004; Bröcheler, Maijoor and van Witteloostuijn, 2004). The corporate demography perspective (Pfeffer, 1983) argues that organizational behavior and performance can largely be explained by studying the demographic features of an organization's personnel. By and large, this literature suggests that the distribution of the personnel's demographic or 'objective' characteristics (in terms of the mean and spread of, e.g., age, education, experience and tenure) is a key determinant of how the organization looks like, what it does, and how it performs. For instance, Pennings, Lee and van Witteloostuijn (1998) provide evidence in a longitudinal study of thousands of Dutch accountancy firms in the

1880 – 1990 period that the accountancy firms' composition in terms of human and social capital is a key *ex post* predictor of their survival (of course, after correcting for a wide range of 'traditional' variables such as industry structure and firm size).

In a similar vein, upper echelon theory (Hambrick and Mason, 1984) argues that the individual features of an organization's key decision makers – i.e., the members of the top management team (TMT), including the Chief Executive Officer (CEO) – cannot be ignored whilst searching for an explanation of their organization's behavior and performance. In addition to the 'objective' demographics from the corporate demography literature, upper echelon theory emphasizes the key role of 'deeper' and 'subjective' features such as attitudes and personalities. For example, research in the past decades into the impact of the CEO's personality has revealed that the locus-of-control trait – i.e., the disposition of perceived control – is a stable predictor of a small firm's performance (e.g., Brockhaus, 1975; Anderson, 1977; Kets de Vries, 1977; Pandey and Tewary, 1979; Brockhaus, 1980, 1982; Miller and Toulouse, 1986; Powell, 1992; Boone, De Brabander and van Witteloostuijn, 1996; Lee and Tsang, 2001). For instance, Boone et al. (1996) reveal in their study of about 40 Flemish furniture firms that the CEO's locus-of-control personality trait is a key determinant of the organization's competitive strategy and financial performance.

The corporate demography and upper echelon perspectives have, to date, produced hundreds of empirical studies, focusing on a wide variety of industries, features and strategies (see, e.g., Finkelstein and Hambrick, 1996, Williams and O'Reilly, 1998, Baum, 2002, and Boone et al., 2005, for overviews). In the context of this research proposal, a conceptual summary of behavioral management suffices. In a nutshell, Figure 1 offers such an overview of this behavioral management research tradition.

[INSERT FIGURE 1 ABOUT HERE]

Here, for the sake of brevity, we focus on the role of the Chief Executive Officer (CEO) only, ignoring the influence of the top management team as a whole (Boone et al., 2004). By and large, four different key effects can be distinguished (next to and on top of many 'traditional' control variables, from market growth to organizational size):

1. Preference effect. CEOs tend to develop clear preferences for particular types of strategy. For example, CEOs with a financial background generally reveal a significant tendency to pursue cost-cutting strategies, rather than their product differentiation counterparts.
2. Strategy effect. Under particular circumstances (say, tough competition), different strategies (e.g., product differentiation) are associated with different performance outcomes (e.g., high profitability).
3. Implementation effect. This relates to leadership effectiveness. Irrespective of the specific strategy pursued, some CEOs are more effective than others – e.g., because they have a good intuition as to how to lead and motivate their workforce.
4. Alignment effect. A particular CEO may be good at carrying out some strategies, but not others. For instance, a CEO with a financial background might be able to perform well with a cost-cutting strategy, but might lack the capabilities to be as successful if the strategy is a more innovation-oriented one.

The current study applies Figure 1's line of thinking to issues of behavioral finance. Figure 2 is an adapted version of Figure 1, providing a behavioral finance content to the overall behavioral management framework.

[INSERT FIGURE 2 ABOUT HERE]

Again, in a nutshell, four different key effects can be distinguished (next to and on top of, as above, many 'traditional' control variables, such as the market's liquidity and

microstructure). Note that, for the time being, the empirical pilot study presented below is restricted to the direct trader features – trading performance nexus, ignoring trader judgment and trading behavior as intermediate variables. That is, how are trader features related to trading performance?

1. Preference effect. It may well be that a particular trader has a preference for a particular type of trading strategy. Perhaps, for example, an experienced trader is more risk averse, and produces less volatility, than a newcomer.
2. Strategy effect. Under particular circumstances (e.g., different microstructures), different trading strategies are associated with different trading outcomes, at the level of the individual trader (e.g., profit) and the market at large (e.g., volatility).
3. Implementation effect. This relates to behavioral effectiveness. That is, irrespective of the specific trading strategy pursued, some traders are more effective than others – e.g., because they have a good sense of timing.
4. Alignment effect. A particular trader may be good at carrying out some trading strategies, but not others. For instance, an individual trader might be able to perform well with risk-seeking speculation, but may lack the capabilities to be as successful if the strategy is a more risk-averse one.

As far as trader features are concerned, the objective and subjective features that have been found to be relevant in the behavioral management literature can be taken on board here as well. For the sake of the argument in the current pilot, emphasizing the value added of cross-pollination with personality psychology generally, we focus on six examples of potentially relevant personality traits: locus of control, maximizing tendency, regret susceptibility, self-monitoring, sensation seeking and type-A/B behavior. Of course, at a later stage, the list of trader features to be measured can and will be be extended.

3. SIX PERSONALITY TRAITS

Building on earlier work in behavioral finance (McInish, 1980, 1982; Chui, 2001; Biais et al., 2005; Fenton-O'Creevy et al., 2005), and in combination with well-established insights from behavioral management (Boone, De Brabander and van Witteloostuijn, 1999a, 1999b; Schwartz, Ward, Monteresso, Lyubomirsky, White and Lehman, 2002; Boone et al., 2005), we decided, as a first step, to explore the impact of six personality traits on trading performance. We used four criteria to guide our decision as to select which traits, out of so many that circulate in the personality psychology literature:

1. The traits have to be easily and reliably measurable with standard scales that are well-established in the psychometric literature.
2. The traits must be real traits – that is, they have to be relatively independent of the individuals' age.
3. The traits need to have clear and, in our context, relevant behavioral consequences.
4. The traits have proved to work well in earlier work in behavioral finance, behavioral management or personality psychology.

With this set of four criteria in hand, we ended up selecting six personality traits, which we will subsequently discuss below: locus of control, maximizing tendency, regret susceptibility, self-monitoring, sensation seeking, and type-A/B behavior. For sure, there are many more traits that we could have selected [such as the (in)famous Big Five; see Fenton-O'Creevy et al., 2005], but this set of six suffices for the exploratory purposes of the current study. Note that, given the exploratory nature of our study, we decided to refrain from formulating explicit hypotheses.[1]

[1] As will become clear below, due to the low number of observations, we had to reduce our set of six separate personality traits to a single profile classification variable anyway.

First, locus of control is an important and well-documented personality trait that refers to individual differences in a generalized belief in internal versus external control of reinforcement (Rotter, 1966). People with an internal locus of control see themselves as active agents. They feel that they are masters of their fates, and they trust in their capacity to influence the environment. Conversely, those with an external locus of control view themselves as relatively passive agents, believing that the events in their lives are due to uncontrollable forces. We chose to study this particular trait because it indicates fundamental differences between individuals (Boone & De Brabander, 1993; Boone, De Brabander, Carree, de Jong, van Olffen, & van Witteloostuijn, 2002). Furthermore, control perceptions appear to be very salient in explaining effective management, and have been included in a few behavioral finance studies (McInish, 1980, 1982; Chui, 2001). Specifically, research into the relationship between CEO locus of control and organizational performance consistently shows that firms led by internal CEOs perform better than firms headed by external CEOs, both in the short run as well as in the long run (Miller and Toulouse, 1986; Boone et al., 1996; and Boone, De Brabander and Hellemans, 2000).

Second and third, we include the related concepts of maximizing tendency and regret susceptibility, which reflect individual differences in maximization as a goal and in sensitivity to regret, respectively (Schwartz et al., 2002). As such, they both represent potential negative psychological effects arising in view of expanded opportunities for choice. While maximizing tendency relates to (positive or negative) effects *prior* to making a choice and during the decision-making process, regret susceptibility relates to psychological effects that emerge *after* the choice has been made. As opposed to satisficers, who purely strive for a solution that satisfies or exceeds their acceptability threshold, maximizers are on the search for the optimum. As a result, proliferation of choice options poses considerable challenges for maximizers because they need to search

them extensively, ideally all of them, in order to be sure to make the best choice. Hence, with an increasing number of options, chances of achieving the goal of finding the optimum decrease. After a choice has been made, doubts are likely to arise in regret-sensitive people whenever they could not fully search all options, both for practical or principle reasons. In addition, an increasing number of choice options may induce people to feel more responsible for "making the right choice" – hence also blaming themselves for decisions that they later perceive as faults. Consequently, previous studies found people to be more open to "exotic" choices when presented as part of an overall smaller bunch of choice options, and, moreover, to be more satisfied after having made a choice (Iyengar and Lepper, 1999, 2000). Iyengar and Lepper (1999; 2000) suggested that avoidance of regret, akin to loss aversion, may be at the heart of these observations.

Fourth, self-monitoring relates to the observation that people differ in the extent to which they observe and control their expressive behavior and self-presentation (Snyder, 1974, 1979, 1987). Individuals high on self-monitoring regulate their expressive self-presentation for the sake of desired public appearances, and are thus highly responsive to social and interpersonal cues of situational appropriate performances (Snyder and Gangestad, 1986). Individuals low on self-monitoring lack either the ability or the motivation to regulate their expressive self-presentations. Their expressive behavior functionally reflects their own enduring and momentary inner states, including their attitudes, traits and feelings. Thus, high self-monitors possess greater social sensitivity than low self-monitors, and low self-monitors are less aware of others' reactions – or, at least, are less concerned with them (Snyder, 1987). Baron (1989) found that high and moderate self-monitors report are more likely to collaborate and to compromise than low self-monitors.

Fifth, sensation seeking is a trait defined by the seeking of varied, intensive sensations and experiences, as well as the willingness to take physical, social, legal and

financial risks for the sake of such experience (Zuckerman, 1979a, 1979b; Feij and van Zuilen, 1984). The concept of sensation seeking and its relation to individual risk-taking behavior has been extensively studied (Zuckerman, 1994). Research in behavior genetics, neuropsychology and psychophysiology has revealed evidence for a substantial genetic determination for sensation seeking (De Brabander, Boone and Gerrits, 1992, 1995). Differences in sensation seeking are related to individual differences in optimal levels of stimulation and arousal. Other research has found sensation seeking to be positively associated with risk-taking behavior such as alcohol and drug use, sports and gambling, or related sensation seeking with different aspects of human life (Thornquist, Zuckerman and Exline, 1991; Glicksohn and Golan, 2001; Bratko and Butkovic, 2003). Hence, individuals differ as to their motivation to experience sensation, which may impact upon their individual risk-taking behavior. High sensation seekers are characterized by a strong need to continuously experience new and varied stimuli. They are therefore inclined to actively seek risky and novel situations. Conversely, low sensation seekers prefer stable, safe and predictable situations because of their low arousal tolerance.

Sixth, type-A behavior is revealed by an individual who is involved in an aggressive and incessant struggle to achieve more and more in less and less time (Friedman and Rosenman, 1974; Friedman and Booth-Kewly, 1987). Type-A persons are characterized by time urgency, interpersonal hostility, aggression, irritability, impatience and a high level of competitiveness (Glass, 1983; Appels, Mulder and van Houtem, 1985; Baron, 1989). Those who have not developed such a behavioral pattern are called type-B individuals. Type-A persons, due to their impatience and competitiveness, are not only less likely to show cooperative behavior than type-B individuals, but also have greater difficulties to learn the most beneficial strategy (Boone et al., 1999b). Related evidence is revealed by Baron (1989), who observes that type-A persons report a higher frequency of conflict with subordinates than their type-B counterparts. Also, type-A individuals are

less inclined to use accommodation as a conflict-handling method than type-B persons. The accommodation conflict-handling mode implies a strong concern for the views of the other side and a somewhat lesser concern with one's own desires (cf. Kabanoff, 1987).

4. EXPERIMENTAL DESIGN AND PROCEDURE

Experimental design

The experimental design is based on Gneezy, Kapteyn and Potters (2003), with a few modifications. The first modification is that we, compared to their study, combine the two levels of their treatment variable (high or low "information frequency") in each session, but vary the order of play (either high-low or low-high). The second modification is that we used questionnaires, accompanying the experiments, in order to capture demographic and personality features of the participants (see below for details: available upon request). Additionally, we introduced a number of minor changes. For instance, we replaced their physical lottery draw, meant to determine the dividends of the assets traded, by a computerized random number draw.

We set up a market in which participants can trade multiple units of a risky asset in a continuous open-book double auction market in a sequence of twelve trading periods. Each unit of the asset is a lottery ticket that, at the end of a trading period, paid 150 (virtual) cents with probability 1/3 and 0 cents with probability 2/3. At the beginning of each period, a trader was endowed with a cash balance of 200 cents and three units of the asset. If a trader bought a unit, the price was subtracted from her or his cash balance, and one unit of the asset was added to her or his portfolio. If a trader sold a unit, the price was added to her or his cash balance and an asset unit was subtracted from her or his portfolio. At the end of the period, the asset expired and its value was revealed through a lottery. Each trader's earnings for the period were equal to: 200 +

[prices received for units sold] – [prices paid for units bought] + [number of units in portfolio at the end of the period] x [value of the asset (0 or 150) as determined by the lottery]. These earnings were transferred to a trader's accumulated earnings, and the next period started with each trader again having a portfolio consisting of 200 cents in cash and three units of the asset. Traders could not use accumulated earnings from earlier rounds to buy assets. Subjects were not allowed to go short in either assets or cash.

The treatment variable was the order of feedback frequency regimes. The feedback frequency variations have been developed to manipulate the period over which participants evaluate outcomes. This may serve to uncover possible myopic loss aversion (MLA). The setting is similar to the individual choice experiments of Thaler, Tversky, Kahneman and Schawartz (1997), and Gneezy and Potters (1997), but in a competitive setting (endogenous price formation). With respect to feedback frequency, there were two different regimes, a ''high-frequency'' (H) and a ''low-frequency'' (L) treatment, as in the experiments by Gneezy et al. (2003). Since the frequency of portfolio adjustment and information feedback is lower in L, the participants in this regime were expected to evaluate the financial consequences of holding units in a more aggregated way than the participants in regime H. If agents are myopic, the horizon in regime L may be three periods, whereas in regime H it will be one period. Such myopia has been argued to induce loss-averse traders to be less willing to hold assets, leading prices of the risky asset to be lower in H than in L (for details see, Gneezy et al., 2003).

In our setup, in the ''high-frequency'' (H) regime, the market opened in each of the twelve periods of the session; and in each period, traders could adjust their portfolio by buying and selling units, as described above. Prior to the start of trading, the draw of the lottery was determined. However, the lottery outcome was revealed to subjects only after trading of that period had finished. At the end of each period, the draw of the period was revealed so traders became informed about the realized value of the asset for

that period (through a message on the computer screen). Subsequently, the next period started. In the ''low-frequency'' (L) regime, the market opened for trading only in the first period of a block of three periods – that is, trading took place only in periods 1, 4, 7, and 10. In each of these trading periods, units were traded in blocks of three. If a unit was bought (sold) at a particular price in period *t*, then a unit was also bought (sold) at that same price in periods *t+1* and *t+2*. Traders fixed their asset holdings for three periods. Prior to the end of trading period *t* (with $t = 1, 4, 7$, and 10), three independent draws determined the values of the units in periods *t*, *t+1* and *t+2*, respectively. Traders were informed about the three realized values simultaneously, but only after the trading period had closed. For example, they may then have learned that the values of the asset in the three periods are 0, 0 and 150, but these three values were not explicitly assigned to a particular period. In the first treatment, participants traded first in the H regime, and subsequently in the L regime (HL); in the second treatment, the order of feedback frequency regimes was reversed (LH).

Procedures

No subject was allowed to participate more than once. Upon entering the lab, a short introduction was read by the experimenter to the participants. By drawing table numbers, the participants were randomly seated behind computer terminals. Instructions were distributed and read aloud. participantts could examine the instructions more carefully, and privately ask questions. Subsequently, two training periods were run during which participants could practice with the market rules. No feedback took place during the training period, which served purely to familiarize the participants with the software. The two trial periods were held before the actual trading started. There was a brief and clear break between the trial and the experimental periods.

During the experiment, all amounts were denoted in cents. Traders could submit bids to buy and orders to sell. All traders were instantaneously informed about all bids and orders submitted to the market. At any time during a trading period, traders could decide to buy at the lowest order or to sell at the highest bid. When a unit was traded, the accepted bid or order was withdrawn from the market, and all traders were informed that a trade had occurred at that price. Units traded one by one: that is, all bids and orders were for one unit only. Traders could submit as many bids and orders to the market as they liked, and could sell and buy as many units as they liked. However, traders could not sell when they had no units in their portfolio, and they could not buy when their cash balance was insufficient. Also, an individual improvement rule was enforced, requiring a new order (bid) price to be lower (higher) than that trader's standing order (bid). An (effective) trading period lasted three minutes in both regimes, H and L.

In regime H, a lottery was conducted at the end of each trading period. To determine whether the asset paid 0 cents or 150 cents in a period, we used a computerized random number generator. The outcome of each draw was announced to the participants via a message on their computer screen (in both treatments). In feedback regime L, the value of the asset was determined for three consecutive periods. We used three individual random number draws. Participants were informed about the realizations of the three lotteries simultaneously after the last of the three periods had passed, and without learning which draw corresponded to which period. In either case, after the value of the units had been determined, participants' earnings for the previous period in H or previous three periods in L were determined. Subsequently, the next trading period started. At the end of period 12, subjects were privately paid their accumulated earnings. The exchange rate for converting hypothetical cents into € at the end of the evening was 0.0025, resulting in an expected payoff to each subject from trading of €26.25. In

addition to their earnings from trading, each subject received €5 for showing up in time for the session.

Participants were recruited from Bachelor and Master courses in different economics programs at the Faculty of Economics of the University of Groningen in the Netherlands in the Autumn term of 2005. Participation was voluntary, as the experiment was not a mandory activity in any course. In total, 34 students participated, equally divided over five sessions (three in regime xx, and two in yy). Of these 34 participants, 29 per cent was female and 71 per cent male, with an average age of 23. The majority of the participants were Dutch (58.8 %), followed by Chinese (26.5 %) as the second largest group. This is also reflected in the ethnical background, with 64.7 per cent having a European background and 35.3 per cent an Asian one. Regarding educational level, 14 per cent had high-level secondary education as their highest education level, and 17 per cent another Bachelor degree. Furthermore, 41.2 per cent was studying for a Bachelor deegree, and the rest for a Master's. This is reflected in the 32.4 percent attending mainly courses of the third Bachelor year and 52.9 per cent attending courses of the first Master year. The participants' specialized predominantly in Finance (76.5 per cent), with Marketing ranking second (23.5 per cent). Moreover, 38.2 per cent had trading experience of some kind, and 32.4 per cent some kind of marketing experience.

Empirical measures

Our dependent variable is *Payment net of participation fee*, which we use as a proxy for trading performance. As outlined in the experimental setup, participants were paid according to their performance in the respective session, in addition to receiving a small show-up fee (of €5). This performance-related reward depended on their trading performance, as well as on their luck – that is, on how often during a particular session a dividend (of 150 virtual cents) was paid for the traded asset.

We explore the impact of six independent variables, reflecting well-established measures of the six personality traits we selected for this study. As we used well-established and well-validated scales, the explanation of our measures can be brief. For further details, we refer to Boone et al. (1999a: for locus of control, self-monitoring, sensation seeking, and type-A/B behavior) and Schwartz et al. (2002: for maximizing tendency and regret susceptibility). *Locus of control* (Cronbach's a = .49) is measured with the Rotter scale (Rotter, 1966), *Maximizing tendency* (Cronbach's a = .44) and *Regret susceptibility* (Cronbach's a =.67) with the Maximization and Regret scales (Schwartz et al., 2002), respectively, *Self-monitoring* (Cronbach's a = .63) with Snyder and Gangestad's improved Sensation Seeking scale (Snyder and Gangestad, 1986), *Sensation seeking* (Cronbach's a = .77), with the updated Sensation Seeking Scale (Zuckerman, 1979, 1994), and *Type-A/B behavior* (Cronbach's a = .72) with the "Student Jenkins Activity Survey" (SJAS) presented by Yarnold, x and y (1986), which is based on the "Jenkins Activity Survey" (JAS) developed by Jenkins, Zyzanski and Rosenman (1979). Note that the values for the Cronbach's a's we find tend to be (much) lower than those reported in the literature, due to the low number (34) of observations in this pilot study. Still, our Cronbach's a's are above the lower limit of acceptability of 0.6 for our type of exploratory research (Hair, Anderson, Tatham and Black, 1998) for *Regret susceptibility*, *Self-monitoring*, *Sensation seeking*, and *Type-A/B behavior.* As we will show below, both other measures – *Locus of control* and *Maximizing tendency* – will be removed from further analyses.

Given our experimental setup in combination with the low number of observations (see below), we decided to limit the number of control variables to three. Each participant's *Age* is measured in years. *Gender* is coded 1 for females, and 0 for males. *Percentage of lucky draws* is calculated, as a percentage, from the number of times the lucky 150 was drawn (see above), ranging from approximately 17 to 53 per cent (very

unlucky to very lucky, respectively). This latter control variable deserves a more detailed discussion, as it turned out to be highly influential in our pilot experiment. With hindsight, by considerably manipulating this variable, we introduced too much noise in our experiment. As a result, luck became too dominant a determinant of trading performance, pushing the impact of the other variables into the zone of insignificance. Therefore, we decided to report two different sets of (OLS) regression results: one with and one without *Percentage of lucky draws* included. Indeed, without *Percentage of lucky draws*, the coefficient estimate for our key personality trait variable (see below) turned from insignificant to clearly significant. Of course, given our experimental design, we cannot be sure whether or not the latter personality trait finding is robust in realistic experimental settings. This is an issue that needs further work in the future.

Personality profiles

We ended up with 34 participants and 32 observations (see below) only. Hence, because we could enter a limited number of variables in our empirical analyses, as a result, we decided to reduce the number of variables by running hierarchical cluster analyses on our six personality traits (cf. Semeijn, Boone, van der Velden and van Witteloostuijn, 2005). We first conducted a Nearest Neighbor Cluster Analysis based on squared Euclidean distance in order to identify outliers. This resulted in the exclusion of two cases. For the remaining 32 cases, we proceeded with a Ward Cluster Analysis, also based on squared Euclidean distance, resulting in the three-cluster solution below.[2] In this way, we estimated whether or not the scores on our six personality traits group together significantly in distinguishable and interpretable clusters, suggesting personality profiles defined by a combination of a number (here six, maximum) of personality traits.

[2] Suitable other hierarchical clustering algorithms yielded similar results for the cluster solution as did k-means clustering for a three-cluster solution. We ran the cluster analyses both with the raw data and based on standardized values with very similar results.

Of course, due to the low number of participants (34) and observations (32), the outcome can only be indicative, at best. However, given the exploratory nature of our empirical study, such an indication offers a fruitful platform for preliminary analyses. Our initial cluster analysis revealed that two of our personality trait variables – *Locus of control* and *Maximizing tendency* – were not discriminating across clusters. Hence, we re-ran the analyses without this pair of variables. The result is the three-cluster – four-dimension (i.e., trait) solution that is listed in Table 1.

[INSERT TABLE 1 ABOUT HERE]

So, four of our six personality traits indeed make a difference, with locus of control being the only exception. The face value of the three personality profiles, interpreting the score differences as to the four personality traits that discriminate across our three clusters, is satisfactory. Looking at the below and above-average scores per cluster, we have the following interpretation.

1. Profile 1 (n = 7) is characterized by individuals that try to avoid regret, have a dislike for sensation seeking, and reveal type-B behavior. Hence, Profile 1 reflects relaxed, risk-averse persons.
2. Profile 2 (n = 19) captures individuals high on self-monitoring and sensation seeking. So, Profile 2 implies self-conscious, risk-loving persons.
3. Profile 3 (n = 6) includes individuals who are associated with clear type-A behavior. Therefore, Profile 3 relates to impatient, highly competitive persons.

Table 2 provides means, standard deviations and correlations.

[INSERT TABLE 2 ABOUT HERE]

Multicollinearity is not an issue. A number of interesting significant correlations emerge. For instance, nicely in line with the interpretation of our personality profiles, sensation seeking and self-monitoring are positively correlated. This provides further evidence for

the face validity of our personality profile classification. We also find gender to be negatively correlated with locus of control – in line with previous findings that, on average, women score lower on this trait – that is, are more likely to be externally minded. Below, therefore, we run preliminary multivariate analyses with this set of three personality profiles as our key independent variables, with *Profile 1* and *Profile 3* included, and *Profile 2* left out as the reference category.

5. PRELIMINARY EVIDENCE

Due to the small sample, we were quite limited in the extent to which we could use more complex statistical methods or larger batteries of variables for investigating our primary research question – that is, the impact of individual participants' demographic and personality features on their trading performance. Among the demographic characteristics, we mainly focused on *Age* and *Gender* as two standard demographic variables.[3] Gender, in particular, has been shown to potentially affect (trading) performance (Barber and Odean, 2001). Running an OLS regression with only these two independent demograhic variables (and a constant) gives the results listed under Model 1 in Table 3.[4]

[INSERT TABLE 3 ABOUT HERE]

Neither the overall model nor of the individual coefficients are significant. This is not surprising given the small sample size, relative homogeneity of the sample, especially in terms of *Age*, and the dominating influence of the *Percentage of lucky draws* (see below).

[3] Not surprisingly, quite a few of the other other objective and demographic variables that we measured through the questionnaire, such as current study year, were positively related with *Age*. By way of robustness check, we included alternative objective and demographic characteristics in regression analyses not reported here, obtaining results similar to the ones in Table 3.

[4] We also ran ANOVA and non-parametric Kruskal-Wallis and Median tests, which yielded results similar to those based on the regression model, but opted for the regression model in order to more comprehensively capture the determinants of trading performance.

Before turning to the full Model 3, which includes all control and independent variables (i.e., demographic features, personality profiles and *Percentage of lucky draws*), we discuss Model 2, which contains both demographic variables and the three presonality profiles in the form of two dummies for *Profile 1* and *Profile 3*. We find that adding the personality perspective enhances the overall model's ability to explain variation in payments considerably. More importantly, the third personality profile, which reflects type-A individuals with a tendency toward impatient, highly competitive behavior, has a significant negative effect on trading performance, compared to the default *Profile 2*. Note that the participants with this third profile were spread over four of our five sessions. *Profile 1* has a positive, though insignificant effect on trading performance.

In Model 3, finally, we added the *Percentage of lucky draws* control variable. This variable accounted for the fact that differences in payment arose not only from differences in participants' trading performance, but also from variation in the number of realized dividend payments (following from the random lottery draw) across sessions. Unfortuantely, in our pilot, this percentage varied widely, ranging from 16 to more than 50 per cent of all lottery draws per session. As a result, this variable has a very strongly positive and highly significant impact on our performance measure, which obscures the comparatively more subtle influences of the personality profiles. Nevertheless, the significance level of the dummy variable for *Profile 3*, though not satisfactory by the standard rules of thumb, does not deteriorate very drastically, even in a sample as small as ours.

6. APPRAISAL

In this paper, we suggested to integrate insights from personality psychology into behavioral finance. To date, behavioral finance has been dominated by cross-pollination with cognitive psychology. Following a long-standing tradition in behavioral

management, we argued that, next to mechanisms suggested by cognitive psychology, personality traits may offer complementary explanations for trader behavior and trading performance. For the sake of the argument, after presenting our general framework, we focused on six examples of such potentially relevant personality traits: locus of control, maximizing tendency, regret susceptibility, self-monitoring, sensation seeking, and type-A/B behavior. Given our low number of observations, we reduced this set of six variable to a three-category personality profile classification, each of which represents a well-interpretable combination of four of our six personality traits. Using this profile classification in preliminary multivariate analyses indeed revealed an interesting finding. That is, Profile 3 individuals perform significantly worse than their *Profile 1* and *Profile 2* counterparts.

The interpretation of this significant result may run as follows. *Profile 3* individuals stand out for their type-A behavior. Apparently, in our noisy setting, such impatient and highly competitive traders are outperformed by their more patient and less competitive counterparts. If this interpretation is correct, one would expect that *Profile 3* persons trade more, given their "competitive impatience", than *Profile 1* and *Profile 2* individuals.

Additionally, we believe that the insignificance of *Locus of control* and *Maximizing tendency*, which dropped out from the cluster analysis, is interesting as well. After all, we are in the early stages of behavioral finance – personality psychology research. Part of the job, therefore, is to find out, step by step, which personality traits do indeed matter, and which do not, perhaps conditional on the setting's microstructure. In our experimental setting, at least, locus of control and maximizing tendency are irrelevant. Of course, whether or not this is a robust finding cannot be judged on the basis of a preliminary pilot study as ours. Future work is needed to further explore this issue.

Of course, we were not able to run full-blown multivariate regression analyses, due to the low number number (32) of obsevations in our pilot study. Another reason for our inability to produce better results is that the experimental setup we used is associated with too much noise. That is, the random variation in the potential returns to trading was so large that the relative impact of other potential derminants of performance (as reflected in dominant effect of the *Percentage of lucky draws* control variable), such as our personality profiles, became too low. In the near future, we plan to replicate the current esxperiment with a much larger number of participants and with a more noise-free experimental setup. Then, we can not only include our full set of personality trait variables, but also a series of other measures that have emerged as relevant and powerful in behavioral management and personality psychology research.

Two examples are educational background (Frank, Gilovich and Regan, 1993; Boone and van Witteloostuijn, 1999) and need-for-closure (Ford and Kruglanski, 1995; Kruglanski and Webster, 1996). Take the example of need for closure, by way of illustration. Need-for-closure relates to an individual's desire to come quickly to a closure in decisions and judgments. It has been characterized as an individual's need to settle for any answer, rather than remain in a state of ambiguity. Need-for-closure has been shown to be triggered by situational context (e.g., time pressure), or dullness of a cognitive task. At the other extreme, individuals with very low need-for-closure exhibit a tendency to postpone decisions. Both conditions carry costs, and need-for-closure especially, has been associated with judgmental mistakes (van Hiel and Mervielde, 2002). Apart from this replication and extension type of work, we would like to conclude with two further suggestions for future work.

First, future work could seek to unravel intermediate mechanisms by exploring the link between treader features and trader judgments. A key argument in the upper echelon literature is that a manager's attitude and judgment are largely determined by her

or his objective and subjective characteristics. For instance, a manager with an internal locus-of-control personality is more likely to develop optimistic judgments than her or his external counterpart, who has an inclination to be pessimistic. Indeed, much research has revealed robust risk attitude – personality linkages. In a behavioral finance setting, we can explore how human features of an individual trader relate to her or his financial judgment. So, the key question is: how can we explain why one trader is better at predicting the future performance of specific stocks than another trader, notwithstanding the fact that both evaluate the same stocks with the same information at hand?

This issue can be studied by making use of an existing panel data set of firms, with rich information about potential performance determinants.[5] Multivariate analyses of a data set like that produces the key performance drivers that significantly affect organizational performance, in either way. That is, in a model with the relevant performance measure as the dependent variable and a list of theory-based performance drivers as the independent variables the appropriate multivariate analyses indicate which coefficient estimates are significant and which are not, including the sign and size of the effects. Subsequently, the judgment of individual traders can be compared with these estimates. This 'distance' measure, being a proxy of the quality of the judgments, is the dependent variable in the next set of multivariate regression analyses that include the individual traders' features as the key independent variables. In this way, we can find out which individual trader characteristics are significantly related to judgmental quality. For example, is a trader's financial background or locus-of-control internality positively associated with the quality of her or his judgments?

Second, of course, the trader features - trading outcomes nexus central in the current pilot experiment can be studied in much more elaborate ways, moving beyond

[5] For this, we can either use a large AMADEUS or DataStream-constructed data set, or longitudinal data bases available as a result of other research projects. As far as the latter is concerned, examples are the Dutch audit and newspaper industries [see, e.g., Pennings et al. (1998) and Maijoor et al. (2004), respectively Boone et al. (2002, 2004)].

the mere replication with a larger number of observations. The trader's judgmental quality is only one, albeit important, intermediate variable. By the end of the day, it is the performance of the trader and the market that really matters. Again, this nicely fits with the upper echelon's tradition to take the manager's or organization's performance as the ultimate dependent variable, the independent variables reflecting an array of manager and team characteristics. Following a study such as Boone et al. (2005), we can design a series of laboratory experiments to study performance-related issues.[6] In a setting like the one used in ther current pilot study, the dependent variables are measures of trader performance (*e.g.*, trading profit) and market outcomes (*e.g.*, price volatility), all derived from the standard finance literature. In addition to that, an array of objective and subjective features of individual traders, as suggested by the behavioral management literature, can be measured.

The new perspective taken here has to do with the selection of independent variables: individual trader features, which can be aggregated at the market level. Then, we can answer a micro-level question such as 'What trader features (*e.g.*, educational background, trading experience and locus-of-control personality) are positively associated with superior trader performance?', and a macro-level one like 'How is the market-level trader feature's mean and diversity related to market performance (*e.g.*, efficiency and volatility)?' Additionally, the intermediate role of trader behavior can be studied (*e.g.*, risk-averse versus risk-seeking trading behavior). The answers to questions like these may depend upon the market's microstructure (*e.g.*, the rules as to the level and timing of information exchange), which can be easily manipulated in a laboratory context. The microstructure issue is particularly interesting, as the experimental design offers the opportunity to test the extent to which specific (sets of) rules of the game may neutralize the impact of (aggregate) trader features. At a later stage, field research can be added by

[6] Boone et al. (1998, 1999a, 1999b, 2002, 2005) offer evidence for the powerful role of personality in a series of experimental studies that relate player features to player behavior and performance.

moving into the ‘real’ world of traders and markets. What can be taken on board from day one, of course, are many other variables that we deem relevant. For example, in a comparative setting, it might be interesting to study the role of ethnical and national background (see, *e.g.*, Boone and van Witteloostuijn, 1999).

REFERENCES

Anderson, C.R. (1977). Locus of Control, Coping Behaviors and Performance in a Stress Setting: A Longitudinal Study. *Journal of Applied Psychology* **62**: 446-451.

Appels, A., Mulder, P. & Houtem, J. van (1985). De validiteit van de Jenkins Activity Survey: Een vragenlijst ter meting van het type A gedrag. *Nederlands Tijdschrift voor de Psychologie* **40**: 474-487.

Barberis, N., A. Shleifer & R. Vishny (1998). A Model of Investor Sentiment, *Journal of Financial Economics* **49**: 307-343.

Baron, R.S. (1989). Personality and Organizational Conflict: Effects of the Type A Behavior Pattern and Self-Monitoring. *Organizational Behavior and Human Decision Processes* **44**(2) 281-96.

Baum, J.A.C. (2002). *Companion to Organizations*, Oxford: Blackwell Publishers.

Barber, B.M. & Odean, T. (2001). Boys will be Boys: Gender, Overconfidence and Common Stock Investment. *Quarterly Journal of Economics* **116**(1): 261-292

Biais, B., Hilton, D., Mazurier, K., & Pouget, S. (2005). Judgemental Overconfidence, Self-Monitoring, and Trading Performance in an Experimental Financial Market. *Review of Economic Studies* **72**, 287-312.

Boone, C.A.J.J., G.R. Carroll & A. van Witteloostuijn (2002). Resource Distributions and Market Partitioning: Dutch Daily Newspapers, 1968 to 1994, *American Sociological Review* **67**: 408-431.

Boone, C.A.J.J., G.R. Carroll & A. van Witteloostuijn (2004). Size, Differentiation and the Growth and Profitability of Dutch Daily Newspapers, *Industrial and Corporate Change* **13**: 117-148.

Boone, C.A.J.J. & B. De Brabander (1993). Generalized versus Specific Locus of Control Expectancies of Chief Executive Officers, *Strategic Management Journal* **14**: 619-626.

Boone, C.A.J.J., B. De Brabander & J. Hellemans (2000). Locus of Control and Small-Firm Performance: A Research Note, *Organization Studies* **21**: 641-646.

Boone, C.A.J.J., B. De Brabander & A. van Witteloostuijn (1996). CEO Locus of Control and Small Firm Performance: An Integrative Framework and Empirical Test, *Journal of Management Studies* **33**: 667-699.

Boone, C.A.J.J., B. De Brabander & A. van Witteloostuijn (1999a). Locus of Control and Strategic Behavior in a Prisoner's Dilemma Game, *Personality and Individual Differences* **27**: 695-706.

Boone, C.A.J.J., B. De Brabander & A. van Witteloostuijn (1999b). The Impact of Personality on Behavior in Five Prisoner's Dilemma Games, *Journal of Economic Psychology* **20**: 343-377.

Boone, C.A.J.J., De Brabander, B., Carree, M., de Jong, G., van Olffen, W. & van Witteloostuijn, A. (2002). Locus of Control and Learning to Cooperate in a Prisoner's Dilemma Game, *Personality and Individual Differences* **32**: 929-946.

Boone, C.A.J.J., B. De Brabander, W. van Olffen & A. van Witteloostuijn (2004). The Genesis of Top Management Team Diversity: Selective Turnover within Management Teams in the Dutch Newspaper Publishing Market in 1970-1994, *Academy of Management Journal* **47**: 633-656.

Boone, C.A.J.J., W. van Olffen & A. van Witteloostuijn (2005). Personality Composition, Leadership, Information Acquisition and Informed Decision Making in Teams: A Simulation Game Study of the Locus-of-Control Personality Trait, *Academy of Management Journal* (forthcoming).

Boone, C.A.J.J. & A. van Witteloostuijn (1999). Competitive and Opportunistic Behavior in a Prisoner's Dilemma Game: Experimental Evidence on the Impact of Culture and Education, *Scandinavian Journal of Management* **15**: 333-350.

Bratko, D. & Butkovic, A. (2003). Family Study of Sensation Seeking. *Personality and Individual Differences* **35**: 1559-1570.

Brockhaus, R.H. (1975). I-E Locus of Control Scores as Predictors of Entrepreneurial Intentions. *Academy of Management Proceedings,* 433-435.

Brockhaus, R.H. (1980). Psychological and Environmental Factors which Distinguish the Successful from the Unsuccessful Entrepreneur: A Longitudinal Study. *Academy of Management Proceedings*, 368-372.

Brockhaus, R.H. (1982). The Psychology of the Entrepreneur. In: Kent, C.A., Sexton, D.L. and Vesper, K.H. (Eds.), *Encyclopaedia of Entrepreneurship.* Englewood Cliffs, NJ: Prentice-Hall: 39-57.

Bröcheler, V., S.J. Maijoor & A. van Witteloostuijn (2004). Auditor Human Capital and Audit Firm Survival: The Dutch Audit Industry in 1930-1992, *Accounting, Organizations and Society* **29**: 627-646.

Chui, P.M.W. (2001). An Experimental Study of the Disposition Effect: Evidence From Macau. *The Journal of Psychology and Financial Markets* **2** (4): 216–222.

Costa, P.T. & McCrae, R.R. (1992a). *NEO PI-R Professional Manual*. Odessa (FL): Psychological Assessment Resources.

Costa, P.T. & McCrae, R.R. (1992b). Four ways five factors are basic. *Personality and Individual Differences* **135**: 653-665.

De Brabander, B., Boone, C. & Gerrits, P. (1992). Locus of Control and Cerebral Asymmetry. *Perceptual and Motor Skills* **75**: 131-143.

De Brabander, B., Boone, C. & Gerrits, P. (1995). On the Relationship between Arousal and Activation, and Sensation Seeking. *Personality and Individual Differences* **18**: 373-384.

Fama, E.F. (1998). Market Efficiency, Long-Term Returns, and Behavioral Finance, *Journal of Financial Economics* **49**: 283-306.

Feij, J. A. & Zuilen, R. W. van (1984). *Handleiding bij de spanningsbehoeftelijst* (SBL). Lisse: Swets & Zeitlinger.

Fenton-O'Creevy, M., Nicholson, N., Soane, E., & Willman, P. (2005). *Traders. Risks, Decisions, and Management in Financial Markets*. Oxford: Oxford University Press.

Finkelstein, S. & D.C. Hambrick, D.C. (1996). *Strategic Leadership: Top Executives and their Effects on Organizations*, St. Paul, MN: West Publishing Company.

Ford, T.E. & Kruglanski, A. W. (1995). Effects of Epistemic Motivations on the Use of Accessible Constructs in Social Judgments. *Personality and Social Psychology Bulletin* **21**: 950-962.

Frank, R.H., Gilovich, T. & Regan, D.T. (1993). Does Studying Economics Inhibit Cooperation? *Journal of Economics Perspectives* **7**(2): 159-171.

Friedman, H. S. & Booth-Kewley, S. (1987). Personality, type A behavior, and coronary heart disease: The role of emotional expression. *Journal of Personality and Social Psychology* **53**: 783-792.

Friedman, M & Rosenman, RH (1974). *Type A behavior and your heart.* New York, NY: Knopf.

Glass, D. C. (1983). Behavioral, cardiovascular, and neuroendocrine responses. *International Review of Applied Psychology* **32**: 137-151.

Glickson, J & Golan, H. (2001). Personality, Cognitive Style and Assortative Mating. *Personality and Individual Differences* **30**: 1199-1209.

Gneezy, U., Kapteyn, A. & Potters, J. (2003). Evaluation Periods and Asset Prices in a Market Experiment. *Journal of Finance* **58**(2): 821-837.

Gneezy, U., & Potters, J. (1997). An Experiment on Risk Taking and Evaluation Periods. *Quarterly Journal of Economics* **112**: 631-645.

Hair, J., Anderson, R., Tatham, R. & Black, W. (1998). *Multivariate Data Anlysis.* 5th ed. London: Prentice-Hall International.

Hambrick, D.C. & P.A. Mason (1984). Upper Echelons: The Organization as a Refection of Its Top Managers, *Academy of Management Review* **9**: 193-206.

Hiel, van A. & Mervielde, I. (2002). Effects of Ambiguity and Need for Closure on the Acquisition of Information. *Social Cognition* **20** (5): 380-408.

Iyengar, S.S. & Lepper, M.R. (1999). Rethinking the Value of Choice: A Cultural Perspective on Intrinsic Motivation. *Journal of Personality and Social Psychology* **76**: 349-366.

Iyengar, S.S. & Lepper, M.R. (2000). When Choice is Demotivating. *Journal of Personality and Social Psychology* **79**: 995-1006.

Jansen, T., Lier, A. van & Witteloostuijn, A. van (2007). A Note on Strategic Delegation: The Market Share Case, *International Journal of Industrial Organization* (forthcoming).

Jenkins, C.D., Zyzanski, S.J. & Rosenman, R.H. (1979). *Jenkins Activity Survey.* New York, NY: Psychological Corporation.

Kabanoff, B. (1987). Predictive Validity of the MODE Conflict Instrument. *Journal of Applied Psychology* **72**(1): 160-163.

Kets de Vries, M.F.R. (1977). The Entrepreneurial Personality: A Person at the Crossroads. *Journal of Management Studies* **14**: 34-57.

Kruglanski, A.W. & Webster, D.M. (1996). Motivated Closing of the Mind: "Seizing"and "Freezing". *Psychologial Review* **103**(2): 263-283.

Lee, D. Y., & Tsang, E.W. K. (2001). The effects of entrepreneurial personality, background and network activities on venture growth. *Journal of Management Studies* **38**: 583-603.

Matthews, G., Deary I.J. & Whiteman, M.C. (2003). *Personality Traits* (2nd ed.). Cambridge: Cambridge University Press.

McInish, T.H. (1980). A Game-Simulation of Stock Market Behavior: An extension. *Simulations and Games* **11**: 477-484.

McInish, T.H. (1982). Individual Investors and Risk-Taking, *Journal of Economic Psychology* **2**: 125-136.

Miller, D. & J.M. Toulouse (1986). Chief Executive Personality and Corporate Strategy and Structure in Small Firms, *Management Science* **32**: 1389-1409.

Pandey, J. and Tewary, N.B. (1979). Locus of Control and Achievement Values of Entrepreneurs. *Journal of Occupational Psychology* **52**: 107-11.

Pennings, J.M., K. Lee & A. van Witteloostuijn (1998). Human Capital, Social Capital, and Firm Dissolution, *Academy of Management Journal* **41**: 425-440.

Pfeffer, J. (1983). Organizational Demography, *Research in Organization Behavior* **5**: 299-357.

Powell, T.C. (1992). Organizational Alignment as Competitive Advantage. *Strategic Management Journal* **13**: 119-134.

Robbins, S.P. (2002). *Organizational Behavior.* Upper Saddle River, NJ: Prentice-Hall.

Rotter, J.B. (1966). Generalized Expectancies for Internal versus External Control of Reinforcement, *Psychological Monographs*, Complete number **609**.

Schwartz, B., Ward, A., Monterosso, J., Lyubomirsky, S., White, K. & Lehman, D.R. (2002). Maximizing Versus Satisficing: Happiness is a Matter of Choice. *Journal of Personality and Social Psychology* **83**(5): 1178-1197.

Semeijn, J., Boone, C., Velden, R. van der & Witteloostuijn, A. van (2005). Graduates' Personality Characteristics and Labor Market Entry: An Empirical Study Among Dutch Economics Graduates. *Economics of Education Review* **24**:67-83.

Snyder, M. (1974). The Self-Monitoring of Expressive Behavior. *Journal of Personality and Social Psychology* **30**: 526-537.

Snyder, M. (1979). *Advances in Experimental Social Psychology.* New York, NY: Academic Press.

Snyder, M. (1987). *Public Appearances/Private Realities: The Psychology of Self-Monitoring*. San Francisco, CA: Freeman.

Snyder, M. & Gangestad, S. (1986). On the Nature of Self-Monitoring: Matters of Assessment. *Journal of Personality and Social Psychology* **51**: 125-39.

Thaler, R., Tversky, A., Kahneman, D. & Schwartz, A. (1997). The Effect of Myopia and Loss Aversion on Risk Taking: An Experimental Test. *Quarterly Journal of Economics* **102**, 647-661.

Thornquist, M. H., Zuckerman, M. & Exline, R. V. (1991). Loving, Liking, Looking and Sensation Seeking in Unmarried College Couples. *Personality and Individual Differences* **12**, 1283–1292.

Williams, K. Y. & C.A. O'Reilly (1998). Demography and Diversity in Organizations: A Review of 40 Years of Research. In: Staw, B. & Sutton, R. (Eds), *Research in Organizational Behavior* **20**: 77-140. Greenwich, CT: JAI Press.

Witteloostuijn, A. van (1998). Bridging Behavioral and Economic Theories of Decline: Organizational Inertia, Strategic Competition, and Chronic Failure, *Management Science* **44**: 501-519.

Witteloostuijn, A. van (2002). Interorganizational Economics, in: Baum, J.A.C. (Ed.) *Companion to Organizations*, Oxford: Blackwell Publishers, 686-712.

Witteloostuijn, A. van (2003). A Game-Theoretic Framework of Trust, *International Studies of Management & Organization* **33**: Issue 2 (Part II: 53-71).

Zuckerman, M. (1994). *Behavioral Expressions and Biosocial Bases of Sensation Seeking.* Cambridge: Cambridge University Press.

Zuckerman, M. (1979a). *Sensation Seeking: Beyond the Optimal Level of Arousal*. New York (NY): John Wiley & Sons.

Zuckerman, M. (1979b). Sensation Seeking and Risk Taking. In: Izard, C.E. (Ed.), *Emotions in Personality and Psychopathology*. New York, NY: Plenum Press: 163-197.

Table 1.

Personality profiles: Descriptives for personality traits in each cluster

Personality trait (score range)	*Profile 1*		*Profile 2*		*Profile 3*	
	Mean	SD	Mean	SD	Mean	SD
Regret susceptibility (1-5)	4.80	.99	4.19	1.19	4.00	.55
Self-monitoring (0-18)	7.50	3.59	10.00	2.40	6.50	2.17
Sensation seeking (0-40)	14.25	2.12	23.44	3.67	18.00	2.53
Type-A/B behavior (0-21)	4.25	1.98	6.44	2.15	12.83	2.14

Table 2.

Descriptive statistics and bivariate correlations

Variables	Mean	SD		Correlations											
				1	2	3	4	5	6	7	8	9	10	11	12
1. *Payment net of participation fee*	27.09	5.07	34	1											
2. *Gender*	0.29	0.46	34	.208	1										
3. *Age*	23.15	2.34	34	-.232	-.069	1									
4. *Percentage of lucky draws*	36.59	13.02	34	.884***	.157	-.111	1								
5. *Locus of control*	12.47	3.02	34	.016	-.341**	.020	.112	1							
6. *Maximizing tendency*	3.85	0.61	34	.128	.146	-.090	.140	.211	1						
7. *Regret susceptibility*	4.24	1.07	34	.027	.130	.283	.000	.250	.237	1					
8. *Self-monitoring*	8.50	3.10	34	.132	.063	.052	.150	-.139	.245	-.046	1				
9. *Sensation seeking*	19.41	5.72	34	.000	-.001	.143	.-069	-.048	.073	.056	.423**	1			
10. *Type-A/B behavior*	7.18	5.72	34	-.456***	.022	-.046	-.449***	.058	-.060	.015	-.312	.038	1		
11. *Profile 1*	n.a.	n.a.	32	.118	-.234	.062	.108	.032	-.008	.271	-.237	-.681***	-.465***	1	
12. *Profile 2*	n.a.	n.a.	32	.171	.187	-.068	.130	-.043	.016	-.126	.489***	.756***	-.209	-.655***	1
13. *Profile 3*	n.a.	n.a.	32	-.349*	.022	.017	-.284	0.20	-.194	-.140	-.359**	-.205	.781***	-.545***	-.277

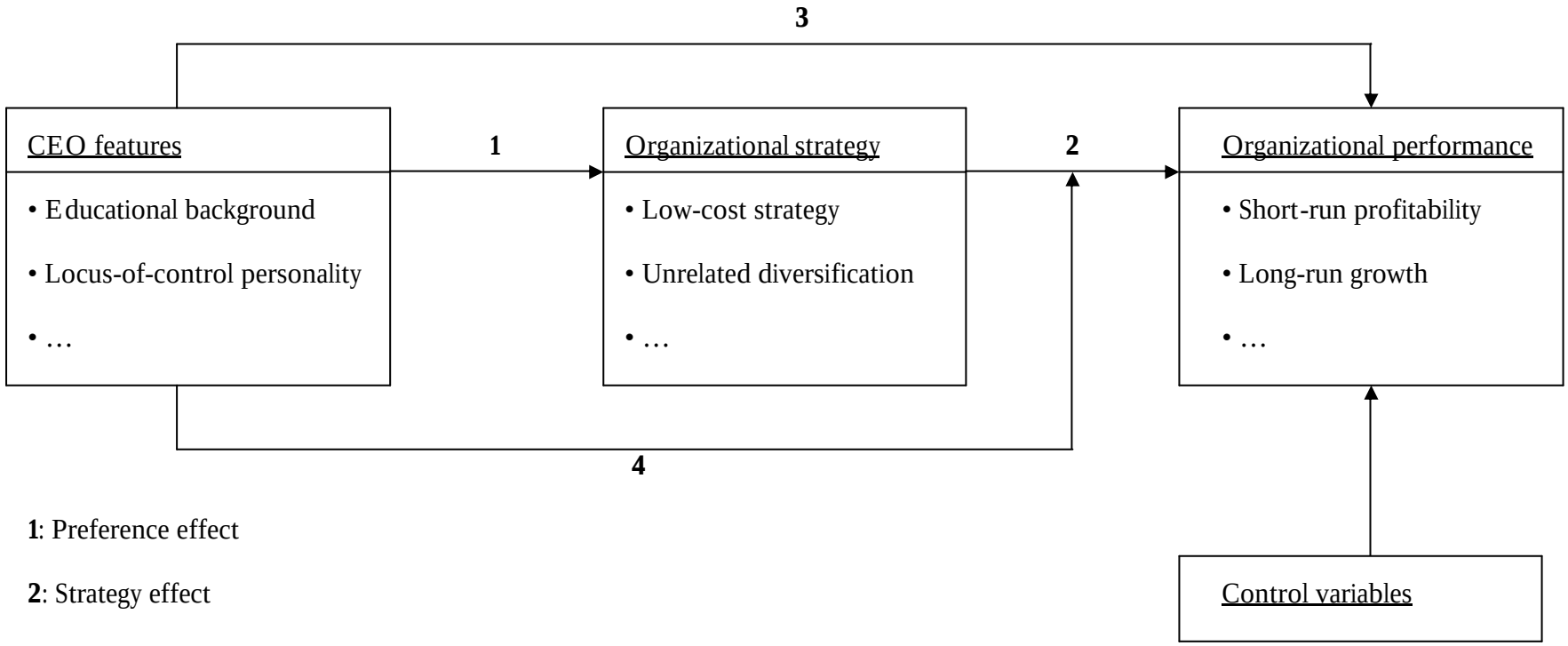
Table 3.

Multivariate regression analyses

Dependent variable: *Payment net of participation fee*	Model 1	Model 2	Model 3
Constant	35.806***	36.069***	22.216***
Gender	2.442	0.356	0.856
Age	-0.417	-0.412	-0.296
Percentage of lucky draws	n.a.	n.a.	0.318***
Profile 1 (dummy)	n.a.	1.159	0.311
Profil 3 (dummy)	n.a.	-4.154*	-1.395
Cases in the analysis	32	32	32
Adjusted R^2	0.035	0.11	0.770
F	1.563	2.002	21.701
P	0.227	0.123	0.000

* p<0.1, ** p<0.05, *** p<0.01

Figure 1: Behavioral management in a nutshell (with examples only)



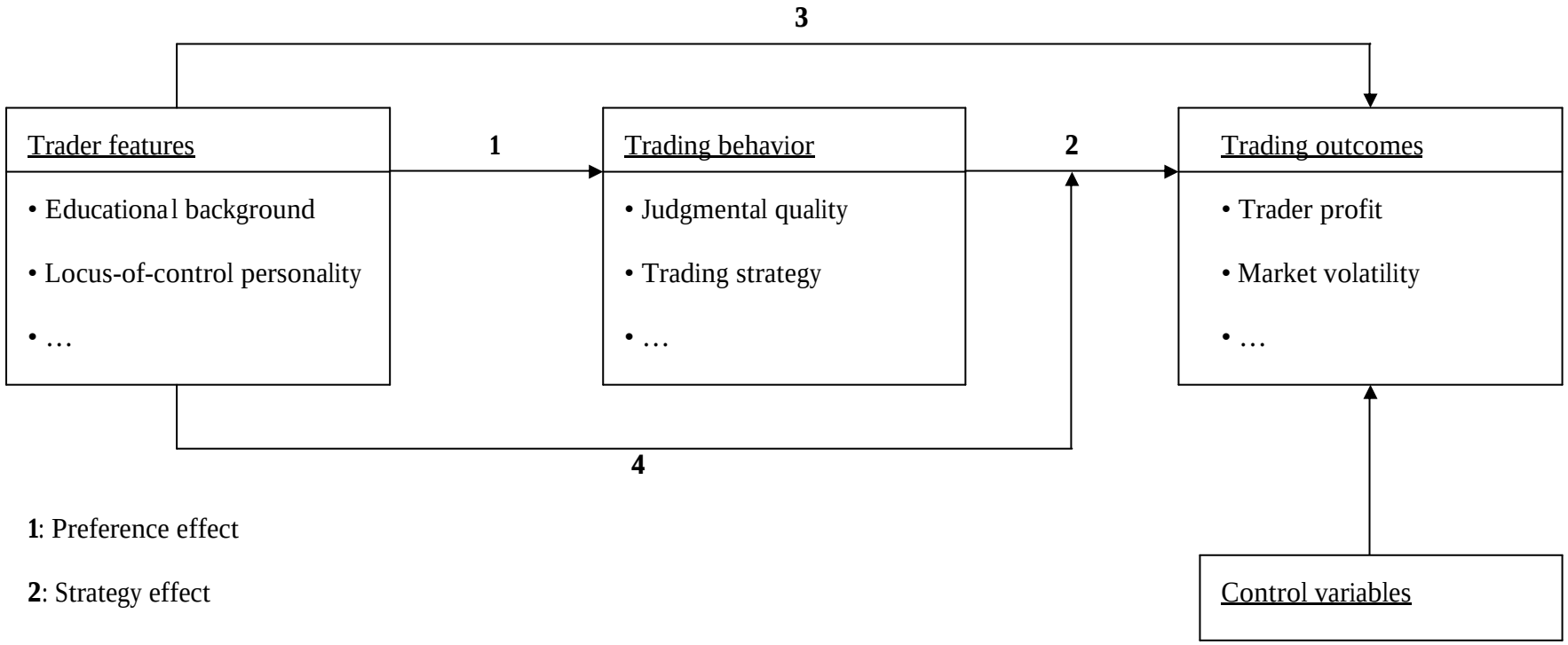
1: Preference effect

2: Strategy effect

3: Implementation effect

4: Alignment effect

Figure 2: A behavioral management application to behavioral finance (with examples only)



1: Preference effect

2: Strategy effect

3: Implementation effect

4: Alignment effect