Unleashing Animal Spirits - Self-Control and Overpricing in Experimental Asset Markets*

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Abstract

One possible explanation for overpricing on asset markets is a lack of self-control abilities of traders. Self-control is the individual capacity to override or inhibit undesired behavioral tendencies such as impulses and to refrain from acting on them. We implement the first experiment that is able to address a potential causal relationship between self-control abilities and systematic overpricing on financial markets by introducing an exogenous variation of self-control abilities. Our experimental treatments seek to detect some of the channels through which individual self-control problems could transmit into irrational exuberance on the aggregate level. We observe a strong effect of inhibited self-control abilities on market overpricing. Our findings are furthermore robust to reducing self-control abilities only for a moderate share of traders in a market. Low self-control traders engage in more speculative behavior early on, but because others imitate their trading patterns, they do not end up earning less and thus are not driven out of the market.

JEL codes: G02, G11, G12, D53, D84

Keywords: Behavioral finance, trader behavior, self control, experimental asset markets, overpricing

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1 Introduction

> "Even apart from the instability due to speculation, there is the instability due to the characteristic of human nature that a large proportion of our positive activities depend on spontaneous optimism rather than mathematical expectations, whether moral or hedonistic or economic. Most, probably, of our decisions to do something positive (...) can only be taken as the result of animal spirits – a spontaneous urge to action rather than inaction, and not as the outcome of a weighted average of quantitative benefits multiplied by quantitative probabilities."[1]
>
> *John Maynard Keynes*

Keynes famously saw "animal spirits" at the root of many (financial) decisions, potentially causing price exaggerations on the aggregate market level. As often in Keynes' work, the term "animal spirits" is not well-delineated. It alludes to optimism, instincts, urges, emotions, and similar concepts. In this paper we assess the notion that a lack of self-control abilities may lead to price exaggerations on asset markets. In psychology, self-control abilities and willpower are defined as the capacities to override or inhibit undesired behavioral tendencies such as impulses and to refrain from acting on them (Tangney et al., 2004). Self-control is necessary to guard oneself against undue optimism, actions motivated by emotional responses, and impulsive decisions. Furthermore, self-control is required in order to stick to plans made in the past.

That self-control is considered relevant for investor success is also evident from statements of well-known investors and from popular guidebooks on the psychology of investing. For instance, Warren Buffet emphasizes that "success in investing doesn't correlate with I.Q. once you're above the level of 25. Once you have ordinary intelligence, what you need is the temperament to control the urges that get other people into trouble in investing."[2] In a study by Lo et al. (2005) involving day traders from an online training program participants stated attributes related to self-control as the most important determinants of trading success.[3] In a similar spirit, Fenton-O'Creevy et al. (2011) report distinct differences in emotion regulation strategies among traders of different experience and performance levels from qualitative interviews with professional traders. Therefore, correlational and anecdotal evidence suggests that self-control matters for trading success on an individual level. The major challenge to overcome is to exogenously vary self-control abilities in order to obtain causal inference on the impact of self-control abilities on behavior and market outcomes. A first step is to use the experimental laboratory and affect *state* self-control levels of traders. Most of the

[1] Source: Keynes (1936), p. 136.

[2] `http://www.businessweek.com/1999/99_27/b3636006.htm`

[3] They quote attributes such as persistence, tenacity, perseverance, patience, discipline, planning, controlling emotions, and (lack of) impulsivity as crucial (Lo et al., 2005, table 3).

available techniques draw on the concept of self-control depletion or exhaustion. Our experimental identification rests on the assumption that self-control is a limited resource and that it is variable over time on the individual level. Evidence for these two characteristics is abundant (e.g. Baumeister et al., 1998; Gailliot et al., 2012). While validated survey measures for *trait* self-control exist, they can only provide correlational inference.

This paper is the first to provide empirical evidence on the causal effects of a variation in self-control abilities on trading outcomes. In the spirit of Keynes we concentrate on aggregate market outcomes in a first experiment and extend our analysis to individual behavior and performance in a second experiment. We use a well-understood financial market setup in the experimental laboratory (Smith et al., 1988; Kirchler et al., 2012; Noussair and Tucker, 2013; Palan, 2013; Eckel and Füllbrunn, 2015) to investigate whether an exogenous variation in self-control abilities of traders leads to overpricing and irrational exuberance. This experimental asset market is known for its basic tendency to exhibit overpricing; it features a dividend-bearing asset with decreasing fundamental value.

In order to deplete self-control abilities before the start of the market, we employ the Stroop task (Stroop, 1935), which is one of the most commonly used tasks in psychology experiments for modulating self-control (Hagger et al., 2010). It is easy to administer, it can be implemented in an exhausting/depleted version and in an easy version, and it allows for additional controls. The majority of studies that use both survey measures and behavioral measures of self-control conclude that the effects of state self-control interventions are qualitatively similar to those of trait self-control levels (e.g. Schmeichel and Zell, 2007). Hence, even if our experiment is confined to the laboratory setting and to a variation in state self-control, it is likely that it extends to real-world situations in which also trait self-control matters.

Our main finding is a significantly higher level of overpricing on markets where traders' self-control abilities have been depleted, compared to markets with traders whose self-control abilities have not been depleted. If markets are populated by depleted and non-depleted traders the effect is similar in size and also highly significant. Obviously, having some self-control depleted traders on a market suffices to create the additional over-pricing effect.

Decision on markets are path-dependent, and traders imitate each other. Hence, it is difficult to rigorously test different trading strategies and transmission mechanisms of our main effect of self-control depletion against each other; most of the choices are endogenous to other choices. Nonetheless, we can refer to some evidence from control variables, from trading and from survey questions that are able to explain the additional overpricing with depleted self-control abilities. First, there is no direct effect of self-control depletion on risk attitudes or cognitive abilities of traders, which could explain our findings. Second, self-control depleted traders do not trade significantly less than non-depleted traders. Third, several indicators show that self-control depleted traders follow stronger speculative motives earlier on when trading. In other words, they contribute more to the creation of the overprice bubble. Fourth, this change in trading strategies is associated with a stronger emotional reaction when being self-control depleted. In short, traders become more impulsive when they cannot resort to their full self-control abilities.

The remaining paper is organized as follows: Section 2 gives an overview of the literature related to our research question, and in section 3, we explain and motivate our experimental design. Consequently, section 4 presents the results from our main experiment, and section 5 reports on an additional experiment that allows us both to test the robustness of our results and to better understand how self-control depletion translates into overpricing and how traders' behavior and decision processes might be affected by the treatment. We discuss potential channels explaining our findings in section 6. Section 7 concludes the paper.

2 Related Literature

In the following we focus on the two aspects in the economics and psychology literature that are most relevant for our study: self-control and experimental asset markets. As already said, self-control abilities and willpower are defined as the capacities to override or inhibit undesired behavioral tendencies such as impulses and to refrain from acting on them. There are different ways to assess self-control abilities and problems in psychology and in economics.

First, self-control can be related to dual-systems perspectives of decision making. As outlined by Kahneman (2011), these perspectives share the general assumption that structurally different systems of information processing underlie the production of impulsive, largely automatic forms of behavior, on the one hand (system 1), and deliberate, largely controlled forms of behavior, on the other hand (system 2). System 2 is effortful and requires self-control resources.[4] Thus, if resources are low, reflective operations may be impaired, leading to a dominance of impulsive reactions that could be in conflict with objective reasoning. From this perspective, reducing self-control abilities can be interpreted as increasing the role of the (impulsive) system 1 in decision making (Hofmann et al., 2009).

Second, and very much related to dual-system perspectives, economists have used dual-self models of impulse control (see, for instance, Thaler and Shefrin (1981) and Fudenberg and Levine (2006)) in order to describe self-control problems.These models study the interaction of two selves, a rational (long-term) and an impulsive (short-term) self. Such models can account for time inconsistent behavior (for instance, as a consequence of quasi-hyperbolic discounting) and for the fact that

[4]Note that the division of system 1 as automatic and system 2 as controlled describes a tendency; there are both automatic and conscious processes involved in exerting self-control and giving in to temptation respectively (cf. Kotabe and Hofmann, 2015).

cognitive load makes temptations harder to resist. Third, also willpower as a depletable resource has been used in models in economics. Ozdenoren et al. (2012) develop a model of consumption smoothing that views willpower as a depletable resource, and Masatlioglu et al. (2014) consider lottery choices.

Is there empirical evidence for self-control abilities or willpower to be indeed limited or depletable resources? In psychology there is plenty of results showing that exerting self-control consumes energy and that it consequently diminishes the available willpower resources for other acts that require self-control.[5] Self-control can involve either cognitive control, or affective control, or both (Hagger et al., 2010). Self-control abilities regenerate through rest, can be trained, and they differ between people (Baumeister et al., 1998; Muraven et al., 1999; Muraven and Baumeister, 2000; Tangney et al., 2004; Muraven, 2010).

Our experimental identification relies on the idea of self-control depletion (see Baumeister et al. (1998)). We reduce self-control abilities by exposing experimental participants to a self-control demanding task before the main task (dual task paradigm). Such setups have been used in other domains in economics, mainly in the context of individual decision making. For example, the consequences of self-control variations in decision making under risk have been studied; however, with inconclusive results: On the one hand, Bruyneel et al. (2009) find that decision makers with reduced self-control take more risks. On the other hand, Unger and Stahlberg (2011) observe an increase in risk aversion after self-control depletion. Bucciol et al. (2011, 2013) show in field experiments with children and adults that self-control depletion leads to reduced productivity in subsequent tasks. De Haan and Van Veldhuizen (2015) find no effect of a repeated Stroop task on the performance in an array of tasks in which framing effects – such as anchoring effects and the attraction effect – are typically observed. Recently, experiments have looked at the effects of self-control variations on other-regarding preferences.Achtziger et al. (2011) report a strong but heterogeneous impact of reduced self-control on offers and accepting behavior in ultimatum games, presumably depending on what an individual's more automatic reactions are. In a similar vein, Achtziger et al. (2015) provide evidence for reduced dictator giving after a reduction in self-control abilities.[6]

Previous studies suggest a relationship between self-control abilities and financial decision making. However, we are not aware of experimental studies in this context. Using survey evidence, Ameriks et al. (2003, 2007) consider the connection between wealth accumulation and trait self-control in a sample of highly educated US households. Ameriks et al. (2003) attribute differences in savings

[5]For recent overviews about the ongoing discussion in psychology and models of the underlying processes involved in self-control refer to Inzlicht and Schmeichel (2012) and Kotabe and Hofmann (2015).

[6]Martinsson et al. (2014) analyze the relationship between self-control and pro-sociality in an indirect way, but their findings are also in line with the idea that pro-social behavior requires self-control.

among households to differing "propensities to plan" – i.e. different individual costs of exerting self-control. Ameriks et al. (2007) use the difference between planned behavior and expected behavior in a hypothetical scenario as a measure for self-control problems. They find a positive correlation between better self-control abilities and wealth accumulation, in particular for liquid assets. Gathergood (2012) conducts a similar study in the UK with a representative sample. He reports a positive association between lower levels of self-control and consumer over-indebtedness.

Our asset market is based on the seminal paper by Smith et al. (1988), who were the first to observe significant overpricing in an experimental double auction market. Many studies have followed up on these early findings.[7] Subject confusion has been considered one of the aggravating factors of overpricing (Kirchler et al., 2012), and Bosch-Rosa et al. (2015) for example show that grouping subjects by cognitive skills leads to increased overpricing for groups with low cognitive sophistication. Nadler et al. (2015) provide evidence that giving testosterone to a group of male participants significantly increases prices.

Since emotion regulation is correlated with self-control abilities (Tice and Bratslavsky, 2000), the influence of emotions on prices in asset markets is also relevant to our research question: Andrade et al. (2015) find that inducing excitement before trading triggers overpricing in asset markets stronger in magnitude and higher in amplitude than other emotions and a neutral condition. In a similar study, Lahav and Meer (2012) show that inducing positive mood leads to higher deviations from fundamental values and thus larger overpricing. The role of emotions in experimental asset markets has also been evaluated using Likert scales (Hargreaves Heap and Zizzo, 2011) and face reading software (Breaban and Noussair, 2013), instead of inducing specific emotions exogenously. Results from these experiments indicate that excitement and a positive emotional state before market opening are correlated with increased prices relative to fundamental values. Moreover, fear at the opening of the market is correlated with lower price levels.

Finally, Smith et al. (2014) analyze neurological correlates of asset market behavior using fMRI. They show that aggregate neural activity in the nucleus accumbens (NAcc) tracks overpricing and that aggregated NAcc activity can predict future price changes and crashes. In their study, the lowest-earning subjects exhibited a stronger tendency to buy as a function of NAcc activity. They also report a signal in the anterior cingulate cortex (ACC) in the highest earners that precedes the impending price peak, and which is associated with a higher propensity to sell. These findings might be related to our experiments, since ACC activation functions can work as an internal "alarm bell" (Smith et al., 2014) that triggers subsequent adjustment, i.e. ACC activation might be a requirement of subsequently exerting self-control (Kotabe and Hofmann, 2015).

[7] Recent surveys can be found in Noussair and Tucker (2013) and Palan (2013).

Figure 1: Treatment Differences in the Stroop Task

3 Experimental Design

Our paper reports on two experiments. The design of Experiment I is described in this section. Experiment II is a natural extension of Experiment I and described in greater detail in section 5. Experiment I consists of four independent parts: (i) instructions and dry runs of the asset market without monetary consequences and without the possibility to build any reputation; (ii) the main treatment variation in self control, the Stroop task (Stroop, 1935) in two versions; (iii) elicitation of risk attitudes and cognitive abilities, both incentivized; and (iv) a fully incentivized asset market.

Our identification of the effects induced by a variation in self-control abilities on market prices relies on the comparison of behavior on markets following two different versions of the Stroop task. A hard version lowers self-control abilities, whereas a placebo version should leave self-control abilities largely unaffected. We implement a condition in which all market participants are subjected to the hard version of the Stroop task (henceforth *LOWSC* for low self-control) and a condition in which all participants were subjected to the placebo version (henceforth *HIGHSC* for high self-control). Except for this treatment variation in part (ii), the two experimental conditions are identical.

The Stroop task followed a simple protocol: participants were supposed to solve as many problems as possible within five minutes. An example of such a problem is displayed on the left-hand side of Figure 1. The task is to select the color of the font the word is printed in. A selection of six color buttons – always the same and in the same order – is given on the bottom right of the screen, and subjects are instructed to click on the correct one. As soon as they made a selection, the next word-color combination appeared. Consecutive word-color combinations always differed from each other. The difficulty of this task is that the words always describe one of the six colors, and that the incongruence between the color of the word and the word itself causes a cognitive conflict, since reading the word is the dominant cue. Common explanations for the conflict are automaticity of reading the word or relatively faster processing of reading than color perception (MacLeod, 1991). The conflict has to be resolved, and resolution requires self-control effort. Applying this effort depletes self-control resources and leaves participants with lower levels of willpower and self-control resources after the five minutes.

The Stroop task is one of the most commonly applied methods to deplete self-control resources (Hagger et al., 2010). It can be easily implemented in a computer laboratory, is straightforward to explain, requires only basic literacy skills, and generates additional data on the number of correctly solved problems and the number of mistakes. The difference between the Stroop task in *LOWSC* and *HIGHSC* is the frequency with which a conflicting word-color combination occurred.[8] All screens in *LOWSC* exhibited such a conflict, while in *HIGHSC* only every 70th screen did. Experimental participants did not receive any information on the frequency of such a conflict, while the instructions for both versions of the task were identical. By having an occasional word-color incongruence in *HIGHSC* we were able to ensure that subjects took the task seriously and had to concentrate. If anything, our setup reduces the potential treatment difference, because in *HIGHSC* some self-control depletion might still take place, making the potential result of a significant difference between the two conditions the more difficult to obtain.

We decided to provide participants with a flat payment of € 3 for the Stroop task in order to signal that we were interested in their performance. We decided against using a piece-rate or any other competitive payment scheme because it would create different wealth levels after the treatment variation that are correlated with the condition. Hence, treatment differences would be potentially confounded with wealth effects.[9] Upon completion of the five minutes, we asked experimental participants about how strenuous they perceived the task on a six-point Likert scale.

Self-control resource depletion can influence several relevant variables on the subsequent asset market. We control for two transmission mechanisms in our design: cognitive ability and risk attitude.[10] Eliciting control variables has to take place after the self-control variation but before the experimental asset market for two reasons: Firstly, if these measures were to follow the asset market, there might be spillover effects due to experiences during the asset market and secondly the effect of our self-control manipulation might wear off since the asset market part of the experiment lasts a considerable amount of time during which self-control could regenerate (Muraven and Baumeister,

[8] The right-hand side of Figure 1 shows an example of congruence between font color and word as often used in the easy Stroop task in *HIGHSC*.

[9] Additionally, Achtziger et al. (2015) found no differences in depletion effects between flat payments and incentivized versions of a related self-control manipulation. We are confident that subjects took the task seriously, as each subject tried at least 114 screens and answered at least 110 items correctly.

[10] For evidence of potential effects of self-control depletion on complex thinking see Schmeichel et al. (2003). As mentioned in the previous section, the evidence on the relationship between self-control abilities and risk attitudes is rather inconclusive. Emotions as a potential transmission mechanism will be assessed in experiment II.

2000). Furthermore, in order to avoid that the self-control variation wears off before the asset market interaction starts, it is indispensable that measuring the control variables does not take much time. Two tasks that fitted this requirement are the Cognitive Reflection Test (CRT) for measuring individual cognitive abilities (Frederick, 2005) and a simple multiple price list lottery design for eliciting individual risk attitudes (Dohmen et al., 2011).

First, our subjects answered the three questions of the standard CRT. It is well-known that CRT responses are correlated with more time-consuming measures of cognitive ability, risk and time preferences (Frederick, 2005), as well as with decisions in a wide array of experimental tasks such as entries in p-beauty-contest games (Brañas-Garza et al., 2012) and performance in heuristics-and-biases tasks (Toplak et al., 2011). Furthermore, recently Corgnet et al. (2014) and Noussair et al. (2014) found that the CRT is a good predictor of individual trader's profits in asset market experiments.[11] Subjects were paid € 0.5 for every correct answer but did not learn their earnings until the end of the experiment.

Second, we elicited individual certainty equivalents (CE) for a lottery using a multiple price list as a measure for individual risk attitudes. Differences in risk attitudes can be a rational reason for trade (Smith et al., 1988) and might explain initial underpricing of assets on the market, thus sparking off later price increases and overpricing (Porter and Smith, 1995; Miller, 2002). Furthermore, Fellner and Maciejovsky (2007) find that more risk averse individuals trade more infrequently. On a single computer screen, our experimental participants had to choose ten times between a lottery that paid either € .20 or € 4.20 with equal probability and increasing certain amounts of money that were equally spaced between the two outcomes of the lottery. Subjects were allowed to switch only once from the lottery to the certain amounts. At the end of the experiment, the computer randomly picked one of the ten decisions of each individual as payoff-relevant and implemented the preferred option, potentially simulating the lottery outcome.

Immediately after the risk elicitation the main part of the experiment, the asset market, opened. The asset market featured a dividend-bearing asset with decreasing fundamental value over ten trading periods in a continuous double-auction market design with open order books following Kirchler et al. (2012), i.e. we use a simplified version of the markets in Smith et al. (1988). Each market consisted of ten traders trading a single dividend-carrying asset over the course of ten periods lasting 120 seconds each.[12] Before the first trading period, half of the subjects in a given market received 1000 points in cash and 60 assets, and the other half received 3000 points in cash and 20 assets as their initial endowment. Assignment to the two initial asset allocations was random.

[11] The CRT is regarded as a measure of cognitive ability and thinking disposition (Toplak et al., 2011). We will discuss the CRT results and their implications in more detail when we discuss our results in section 6.

[12] Appendix A.8 provides the experimental instructions, including a screen shot and a description of the trading screen.

During each trading period, traders could post bids and asks as well as accept open bids and asks. Partially executed bids and asks continued to be listed with their residual quantities and inactive orders remained in the books until the end of the current period. At the end of every period, the asset paid a dividend of either ten or zero experimental points with equal probability. The dividend was added to each trader's cash holdings. Assets had no remaining value after the last dividend payment, i.e. they displayed a declining (expected) fundamental value. This design feature was explicitly stated and highlighted in the instructions. To make things clear, the instructions provided a detailed table with the sum of remaining expected dividend payments per unit of the asset at any point in time. Assets and cash were carried from period to period. Short selling and borrowing experimental points were not allowed. After every period, the average trading price as well as the realizations of the current and all past dividends were displayed on a separate feedback screen. At the end of the ten periods, experimental points were converted into euros, using an exchange rate of 500 points = € 1 .

At the end of the experiment, subjects learned about their payoffs from all parts of the experiment. We asked them to fill in a short questionnaire concerning demographics and background data. We also asked participants how tired they felt after the experiment and as how strenuous they had perceived the entire experiment on a 6-point Likert scale. Then, all earnings were paid out in private and the subjects were dismissed from the laboratory. Experiment I was conducted in October 2013. 160 participants took part in ten experimental sessions. Hence, we obtained 16 independent observations, eight for each of our treatment conditions. The experiment was programmed using z-Tree (Fischbacher, 2007), and recruitment was done with the help of ORSEE (Greiner, 2004). Experimental sessions lasted for about 90 minutes, and participants earned € 18.18, on average. We only invited students who had never participated in an asset market experiment before. We also excluded students potentially familiar with the CRT or the Stroop task.[13] Prior to the start of the experiment, subjects received written instructions for all parts of the experiment (see Appendix A.8). These were read aloud to ensure common knowledge. Remaining questions were answered in private.

4 Experimental Results

4.1 Manipulation Check

The data suggests that our treatment manipulation was successful: First of all, during the Stroop task participants tried so solve fewer words, had fewer correctly solved words and committed more

[13] Of our 160 subjects, one suffered from some form of dyschromatopsia, i.e. a color vision impairment. We asked for it in the post-experimental questionnaire in order to make sure that it is not a common phenomenon among our participants.

mistakes in the *LOWSC* condition than in the *HIGHSC* condition (Mann-Whitney tests all $p <$ 0.01).[14] Additionally, participants perceived the Stroop task as significantly more strenuous in the *LOWSC* condition than in the *HIGHSC* condition (Mann-Whitney test $p < 0.01$). Finally, we do not find any differences in background characteristics such as field ($p = 0.416$) and year of study ($p = 0.9162$), age ($p = 0.1709$) and gender ($p = 0.9558$) across our treatments (Mann-Whitney tests and Pearson's χ^2 test for field of study), suggesting that random assignment to treatments was successful.

4.2 Definitions and Measures

To calculate mean prices one can use an adjustment that takes trading volume into account (henceforth: volume-adjusted prices) or an adjustment that takes the number of trades into account (henceforth: trade-adjusted prices). The former is an average price per asset, whereas the latter is an average price per trade. Our results remain unaffected by the choice of adjustment; in line with the literature, we mainly display results based on volume-adjusted prices.

In order to quantify the tendency of markets to exhibit irrational exuberance we compare trading prices with the fundamental value of the asset. In the following we adopt the approach of Stï¿½ckl et al. (2010) and assess the market price developments using *Relative Absolute Deviation* (RAD) (in equation 1) and *Relative Deviation* (RD) (in equation 2) as measures for general mispricing and overshooting, respectively.

$$\text{RAD} = \frac{1}{T}\sum_{t=1}^{T}\frac{|P_t - FV_t|}{\bar{FV}} \tag{1}$$

$$\text{RD} = \frac{1}{T}\sum_{t=1}^{T}\frac{P_t - FV_t}{\bar{FV}} \tag{2}$$

where P_t is the volume-adjusted mean price in period t, FV_t is the fundamental value of the asset in period t and $\bar{FV}$ denotes the average fundamental value of the asset over all periods.

RAD is constructed as the ratio of the average absolute difference of mean market price and fundamental value relative to the average fundamental value of the asset. RD is the ratio of the average difference between mean market price and fundamental value relative to the average fundamental value. The difference between the two measures is how the difference between mean market price and fundamental value enters the calculation: For RAD the difference enters in absolute terms, thus all deviations from the fundamental value – either overpricing or underpricing – increase RAD, making RAD a measure of average mispricing. For RD the wedge between market price

[14]Detailed distributions on these variables can be found in section A.4 of the appendix. All tests reported in this paper are two-sided, unless otherwise noted.

and fundamental value retains its sign, thus periods with overpricing and underpricing can cancel each other out. Hence, RD provides the dominant direction of mispricing, making it a measure of average overpricing.

Both measures are straightforward to interpret: A RAD of .1 means that prices are on average 10% off fundamental value, while a RD of .1 indicates that prices are on average 10% above fundamental value. Both measures are independent of the number of periods as well as fundamental value, and increase in the difference of market prices and fundamental value.

4.3 Aggregate Price Development

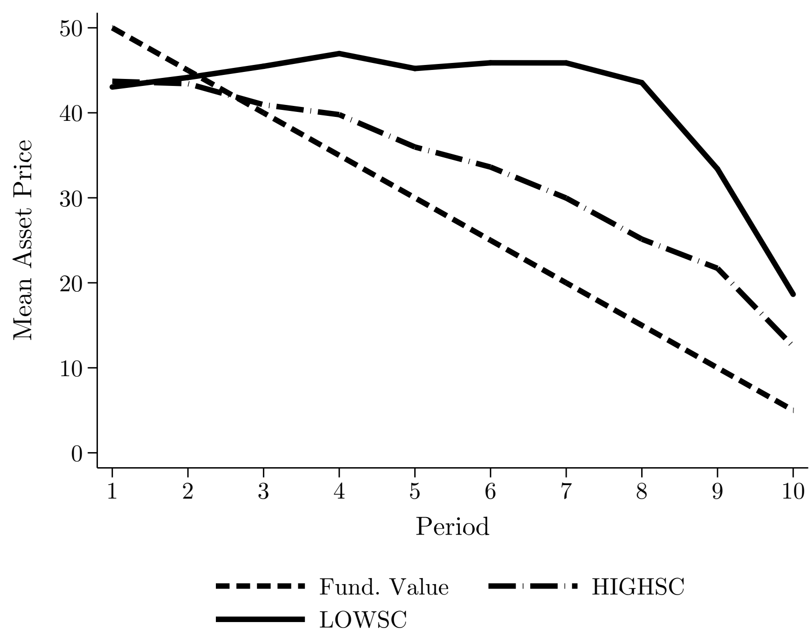

Figure 2: Mean (Volume-adjusted) Trading Prices in the two Treatments

Figure 2 shows how average market prices in *LOWSC* and *HIGHSC* evolve over time. In both conditions, average market prices start out at a similar level, displaying a moderate level of underpricing. However, from the third period onwards, average prices in both conditions exceed fundamental value. Eventually, average market prices drop sharply, but do not drop below fundamental value again.

The most conservative comparisons between the two treatments are based on market averages over all traders and over all ten periods. This is the approach we apply for all tests regarding aggregate market outcomes. These averages are strictly statistically independent, and test statistics are based on eight observations in each treatment. A Wilcoxon signed-ranks test confirms the impression from eyeballing, i.e. that market prices in both conditions are significantly different from fundamental value (*HIGHSC*: $p = 0.0929$, *LOWSC*: $p = 0.0173$). Figure 2 suggests more pronounced overpricing in the *LOWSC* condition which is confirmed by a Mann-Whitney test ($p = 0.0742$).

Concerning our measures for mispricing and overpricing, we find that markets in the *HIGHSC* condition exhibit an average RAD of 0.3253 and an average RD of 0.1885, while in the *LOWSC* condition we observe an average RAD of 0.5890 and an average RD of 0.4990.[15] According to RAD, prices in the *HIGHSC* condition deviate by about 33% from fundamental value, whereas they deviate by about 59% from fundamental value in the *LOWSC* condition. The difference between RAD in the two treatments is significant (Mann-Whitney test, $p = 0.0460$). A comparison of RD tells us that while in *HIGHSC* overpricing is on average 19%, in *LOWSC* prices exceed fundamental value by almost 50%. A Mann-Whitney test suggests that RD is also significantly different between the two conditions ($p = 0.0742$). Thus, trade among individuals with low self-control leads to overpricing which is more than twice as high as in the baseline *HIGHSC*.

Since RAD and RD are comparable across studies, we can use our results and compare them to the findings of Kirchler et al. (2012), who use an almost identical version of our asset market. They report RAD = 0.414 and RD = 0.297 for their baseline market. Using Wilcoxon one-sample signed-rank tests, we do not find a difference between their result and our *HIGHSC* condition ($p = 0.2626$ for both RAD and RD), but our *LOWSC* treatment exhibits substantially more mis- and overpricing ($p = 0.0929$ for RAD and $p = 0.0499$ for RD). We are thus confident, that the results of our *HIGHSC* condition are no outliers, but replicate results commonly found in the literature.

Figure 3 displays the price evolution of single markets in the two conditions. It is noticeable that there is also a high degree of endogeneity in price evolution and a lot of heterogeneity among markets in the same condition. The left panel represents the markets from the *HIGHSC* condition, while the right panel shows the *LOWSC* markets. Price paths in *HIGHSC* markets often display a rather flat or declining development. Strikingly, in *LOWSC* a number of markets display a hump-shaped price evolution that initially increases, peaking in the second half of the trading periods. The emergence of overpricing can oftentimes be attributed to constant prices despite decreasing fundamental values (Huber and Kirchler, 2012; Kirchler et al., 2012) which fits price paths in *HIGHSC* markets more than in *LOWSC* markets.[16]

[15] Both measures are significantly different from zero for both conditions.

[16] Section A.1 in the appendix shows a comparison of overpricing measures across treatments for each period independently. Overpricing in *LOWSC* significantly exceeds overpricing in *HIGHSC* in periods 6-9.

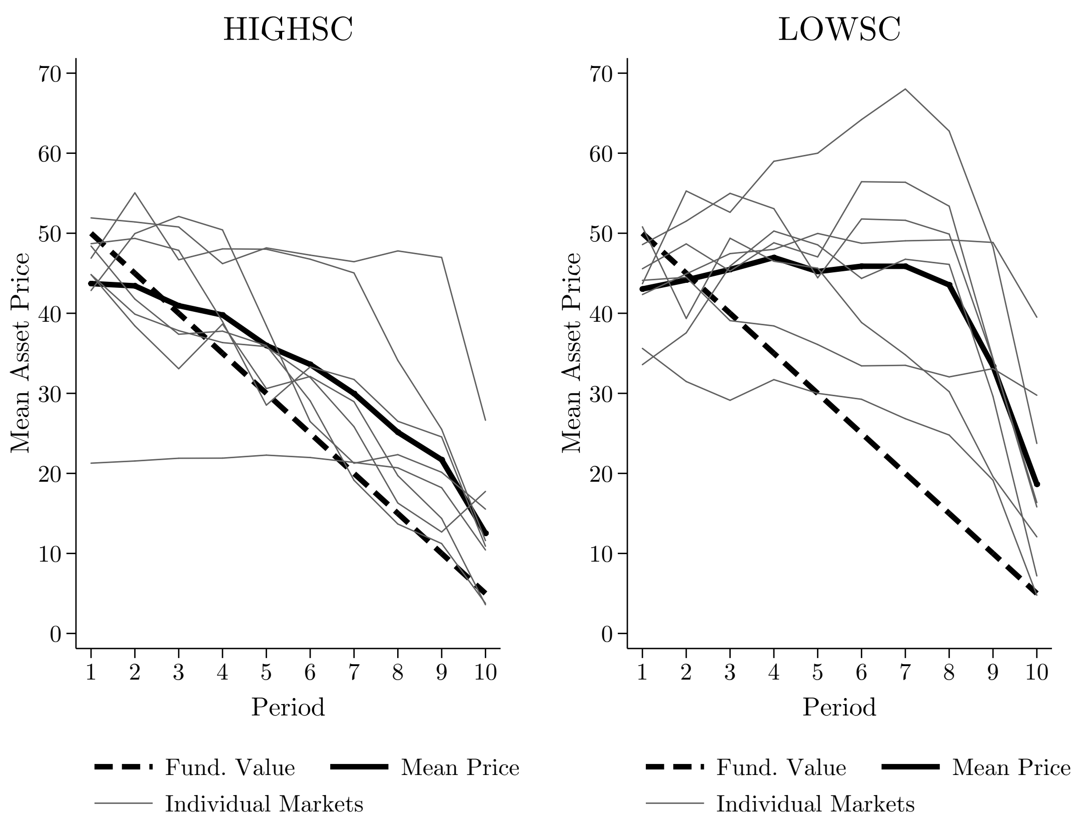

Figure 3: Evolution of Individual Market Prices in *HIGHSC* and *LOWSC*

4.4 Potential transmission mechanisms of the treatment effect

Having established a significant treatment effect, the next step is to look at potential channels via which self-control variations could have an effect on market outcomes. Detailed descriptive results on the variables considered in this section can be found in sections A.5ff. of the appendix.

4.4.1 Cognitive Abilities and Risk Attitude

Self-control depleted participants might not be willing to think as hard and thus provide the (wrong) intuitive answers in the CRT. The average number of correct answers in the CRT was 1.05 in *HIGHSC* and 1.14 in *LOWSC*. The difference in CRT score between the two conditions is not significant according to a Mann-Whitney test ($p = 0.7223$). Therefore, we are confident to say that the Stroop task did not have an impact on our incentivized version of the CRT.[17]

Some authors have speculated about a relationship between risk aversion and overpricing (Porter and Smith, 1995; Miller, 2002). Trader activity has been found to be negatively correlated with risk aversion (Fellner and Maciejovsky, 2007). The average certainty equivalent we elicited is close to the lottery's expected value: 2.2 in *HIGHSC* and 2.15 in *LOWSC*. While the literature exploring the effect of reduced self-control on risk aversion has come to ambiguous results (Bruyneel et al., 2009; Unger and Stahlberg, 2011), we find no significant effect (Mann-Whitney test, $p = 0.4083$) on risk aversion as measured by our certainty equivalent elicitation.

4.4.2 Trading Activity and Exhaustion

An additional channel through which our results could be explained is changes in trading activity, i.e. the number of traded shares per period. People low in self-control have been reported to become more passive (Baumeister et al., 1998, Experiment 4). Increased passivity and thus a thinner market in *LOWSC*, where few trades could drive overpricing, can potentially be responsible for our results. Thus we compare the number of shares traded in each condition. Figure 4 illustrates the evolution of average shares traded per period. Traders in *HIGHSC* traded slightly more overall: while the average trader traded 13.02 shares per period in *HIGHSC*, only 11.39 shares changed hands on average per trader in each period in *LOWSC*. However, according to a Mann-Whitney test, there is no significant difference between amounts traded across conditions ($p = 0.3446$).[18]

To rule out changes in fatigue as causing our results we utilize measures from our questionnaire which was run at the end of the experiment. Remember that self-reports indicate that participants find the *LOWSC* condition significantly more strenuous than the *HIGHSC* condition. Does that

[17] If we include the observations from our second experiment, the CRT scores of the two groups become 1.0875 and 1.1375 respectively with $p = 0.7442$ from a Mann-Whitney test. Similar results hold for the other tests in this section.

[18] An additional regression analysis in Table 6 in appendix A.2 confirms these findings.

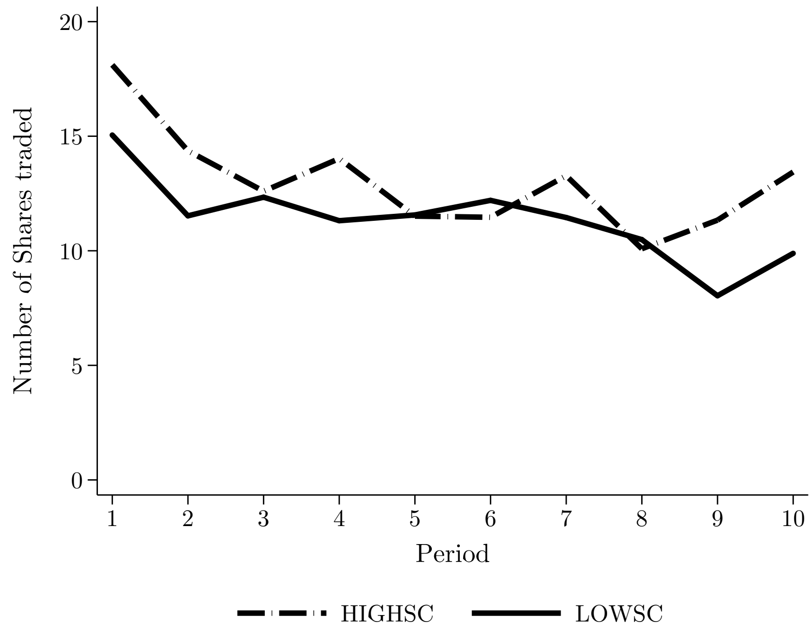

Figure 4: Evolution of Average Shares Traded per Trader by Condition

translate into participants being more tired? Answers to a survey question suggest otherwise. Subjects whose self-control had been reduced do not report to be significantly more tired at the end of the experiment (2.8 in *HIGHSC* vs. 2.99 in *LOWSC*, Mann-Whitney test: $p = 0.4926$).

4.4.3 Regressions controlling for Potential Channels

Although our control variables seem to not have been affected by our treatment, they could still possess explanatory power for the difference in overpricing that we observe. We therefore run regressions, including those controls as indepedent variables. To avoid endogeneity problems across trading periods and between subjects respectively, we aggregate overpricing measures over all periods on the individual level and use robust standard errors clustered at the market level. We do this separately for sales and purchases, since selling above fundamental value results in an expected profit, while buying above fundamental value results in an expected loss. We define measures for individual overpricing for purchases and sales, which we call $IndRD_{purchases}$ and $IndRD_{sales}$ respectively. Similar to the measure RD they are defined as the percentage of buying (selling) prices exceeding the asset's fundamental value pooled over all periods, but for each subject's buying (selling) activity separately instead of on the market level. We report results on $IndRD_{purchases}$ which is the dependent variable in our regressions in Table 1. In appendix A.2, we provide robustness checks for our chosen approach for sales and both sales and purchases aggregated.

	(1)	(2)	(3)	(4)
		$IndRD_{purchases}$		
LOWSC	0.369**	0.375**	0.900***	0.911***
	(0.136)	(0.131)	(0.124)	(0.112)
CRT		-0.0725**	-0.0861**	-0.0802**
		(0.0301)	(0.0366)	(0.0347)
CE		-0.00916	0.0943	0.0972
		(0.0516)	(0.0612)	(0.0605)
CRT × *LOWSC*			0.0324	0.0334
			(0.0552)	(0.0537)
CE × *LOWSC*			-0.258***	-0.263***
			(0.0722)	(0.0697)
Female				0.0683
				(0.0529)
Constant	0.0839	0.180	-0.0331	-0.0918
	(0.0822)	(0.111)	(0.0699)	(0.0770)
Observations	160	160	160	160
R^2	0.227	0.265	0.327	0.334

OLS regression, dependent variable is Individual Relative Deviation (IndRD) for purchases, an individual equivalent to market level Relative Deviation (RD) restricted to purchases only. *LOWSC* is a dummy where 1 stands for *LOWSC* and 0 for *HIGHSC*. CE is an individual's certainty equivalent. CRT denotes the number of correct answers on the CRT. Heteroskedasticity robust standard errors clustered at market level in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Table 1: Determinants of individual RD based on purchases

In all four models we are interested in the effect of the explanatory variables on $IndRD_{purchases}$, our measure of individual overpricing. Throughout all specifications, we observe a significant treatment effect: Being in *LOWSC* increases an individual's propensity to buy at excessive prices substantially. In specification (2) our measure for risk attitude is not significant, but if we also include interactions with our treatment in specifications (3) and (4), risk seeking is correlated with lower individual overpricing when self-control capabilities are reduced. Performance on the CRT has the expected effect of reducing buying at prices above fundamental value in all specifications where it is included and its effect does not significantly differ between participants in *LOWSC* and *HIGHSC* markets. Hence, introducing measures for risk aversion and cognitive skills and their interactions with our treatment do not reduce the treatment coefficient which remains highly significant. Therefore we are confident that neither changes in cognitive skills nor in risk preferences alone are responsible for our results.

5 Experiment II: Mixed Markets

5.1 Motivation

The results reported in section 4 referred to markets, in which either all market participants underwent the hard Stroop task or none of them, i.e. either everyone's self-control resources had been reduced or noone's. In this section we report results from markets, in which only half of the participants' self-control was weakened. Each market consisted of 5 participants randomly assigned to the easy Stroop version from the *HIGHSC* condition and 5 participants randomly assigned to the hard Stroop version from the *LOWSC* condition. We call this new condition *MIXED* and for simplicity refer to traders facing the hard version of the Stroop task as *MIXLO* traders and to those facing the easy version of the Stroop task as *MIXHI* traders. The motivation for this additional treatment is twofold. Firstly, since in a real world setting it is likely that individuals high and low in self-control interact,[19] we want so see whether the effect of reduced self-control observed in *LOWSC* markets can be replicated with a smaller share of depleted subjects in *MIXED* markets. Secondly, asset market experiments are zero sum games and behavior is highly endogenous to market prices which makes it technically impossible to analyze differences in behavior resulting from reduced self-control in our pure markets. Therefore, we wanted a condition, where traders under both conditions are active at once in order to test for differences in trading behavior and performance. We conducted 8 additional sessions with 16 markets in April 2014 and November 2015. In the last four sessions we added several questions to the questionnaire dealing with participants' emotions. We were inter-

[19]This might be due to dispositional differences in self-control (trait) or due to differential previous demands on self-control resources between traders (state).

ested whether our variation of self-control had taken effect via changes in emotional states. In order to reduce experimenter demand effects and as is common in experiments analyzing emotions, we confronted subjects with several emotions of which some were not linked to our question of interest. Apart from the assignment to the respective version of the Stroop task and the additional questions in the questionnaire of the last four sessions, the experimental protocol remained exactly the same as in experiment I.

5.2 Aggregate Price Evolution

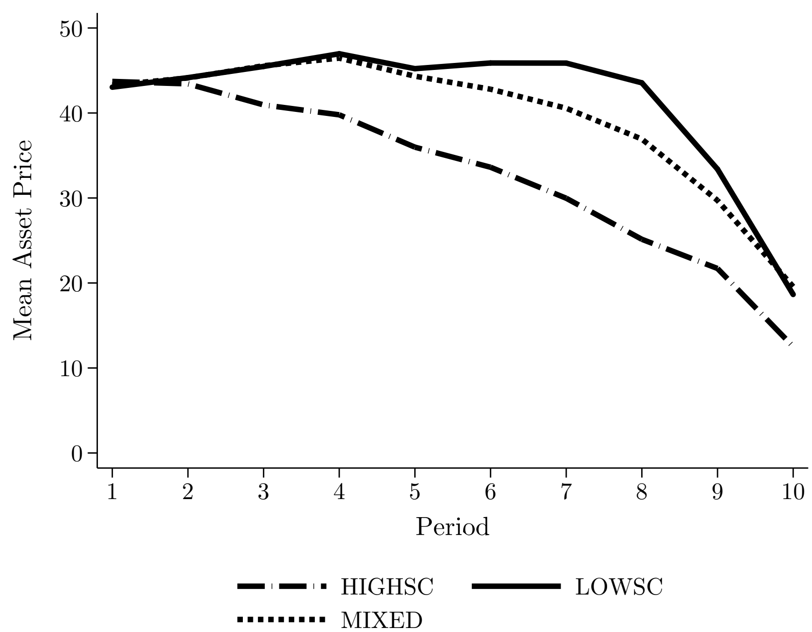

Figure 5: Trading Price Evolution including *MIXED*

Figure 5 shows the evolution of average trading prices in all three treatments. Interestingly, the effect of reduced self-control on mispricing and overpricing does not seem to be reduced if just a part of the trader population is treated. Both *LOWSC* and *MIXED* on average display more overpricing than *HIGHSC*. For *MIXED* we observe an average RAD of 0.551 and an average RD of 0.430. A Mann-Whitney test confirms that the mispricing measure RAD in *MIXED* is significantly different from *HIGHSC* ($p = 0.0500$) but cannot be statistically distinguished from *LOWSC* ($p = 0.8065$). This result also holds for our overpricing measure: RD in *MIXED* significantly differs from *HIGHSC* ($p = 0.0864$), but not from *LOWSC* ($p = 0.5006$).[20]

[20]This also holds when looking at quantity- or trade-adjusted mean prices.

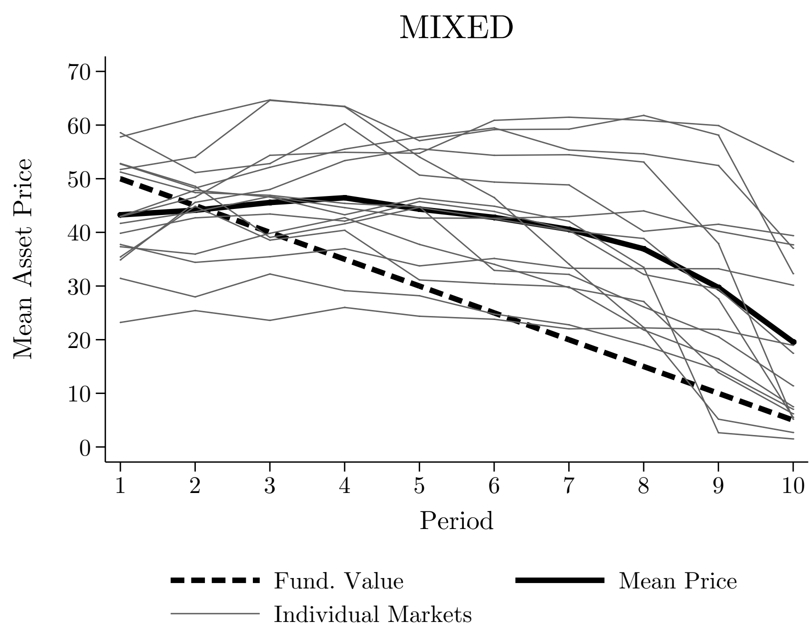

Figure 6: Price Evolution in Individual Markets in *MIXED*

Figure 6 illustrates the evolution of mean trading prices for the 16 individual markets, which were subjected to the *MIXED* condition. Qualitatively, we get similar results as in *LOWSC* that in some of these markets prices exhibit a hump-shaped development, initially increasing and peaking in some intermediate period. Thus already the presence of a moderate share of traders with lower self-control capabilities is sufficient to reproduce the massive overpricing we observed when all traders' self-control was depleted.

5.3 Differences in Trading Behavior & Outcomes

5.3.1 Trading Behavior

Differences in market outcomes in the *MIXED* condition compared to *HIGHSC* markets must result from different actions of *MIXLO* participants. However, when analyzing trading behavior, finding significant effects is particularly difficult, as markets are highly path-dependent and trading behavior is endogenous. A particular deviation in behavior by some subjects in the early phases of a market might shift behavior of other (untreated) traders. We therefore focus on the first trading period, where it is most likely to detect specific forms of behavior that spark off overpricing.[21] Table 2 compares several variables concerning trading activity between *MIXLO* and *MIXHI* traders. Re-

[21]We report rank correlations of first period average behavior with average RD in *MIXED* markets in Table 13 of the appendix. The behavioral differences observed between *MIXHI* and *MIXLO* in the following are in line with being associated with higher degress of overpricing being triggered by *MIXLO* participants.

member that we conduct all tests at the most conservative level and hence uncovering significances using only few observations is particularly challenging.

Table 2: First Period Differences in Trading Behavior

	Group Mean		
	MIXHI	*MIXLO*	p-value
$\overline{p_{bid}}$	36.377	28.487	0.035**
$\overline{p_{ask}}$	49.931	54.478	0.196
$\overline{q_{bid}}$	16.109	17.788	0.660
$\overline{q_{ask}}$	14.389	15.202	0.796
$\overline{time_{bid}}$	59.575	73.000	0.017**
$\overline{time_{ask}}$	69.770	69.617	0.796
$\overline{firsttime_{bid}}$	68.483	80.154	0.048**
$\overline{firsttime_{ask}}$	85.365	85.565	0.959

Variables starting with a p denote prices, q quantities and time variables refer to the time remaining in the current period, thus higher values indicate earlier behavior. *bid* and *ask* refer to posted bids and asks, p-values from Wilcoxon signed-rank tests with data collapsed on market and treatment level, *** p<0.01, ** p<0.05, * p<0.1

According to Wilcoxon signed-rank tests *MIXLO* traders make significantly lower bids initially ($p = 0.035$) and post these bids earlier than their unaffected peers ($p = 0.017$).[22] They are also quicker in posting their first bid at the beginning of the period ($p = 0.048$). While not significant, there also seems to be the tendency that affected traders (while bidding low) ask for a higher price than the *MIXHI* traders ($p = 0.196$). After period one, these differences vanish, suggesting that unaffected traders start imitating this behavior. This in turn suggests an initially stronger speculative motive among affected traders, trying to buy lower and sell higher than their untreated opponents. From period 2 on however, their behavior has incited non-treated participants to behave similarly and hence shifted markets to an entirely different trajectory.

5.3.2 Profits

On average, *MIXLO* traders earned € 8.16 while *MIXHI* traders earned € 7.84 during the asset market, a difference, that is not significant (Wilcoxon signed-rank test, $p = 0.9794$). Since *MIXLO* traders might react differently in more extreme situations, we also looked at RD as a determinant of profits for *MIXLO* and *MIXHI* traders respectively. There is however also no clear correlation between the extent of overpricing and profits for either of our two treatment groups. We consider this as evidence, that inhibited self-control capabilities affect overpricing, but that affected traders

[22] Note that according to Table 13 of the appendix, the average bidding time is the best predictor of aggregate overpricing over all periods out of the variables of first period behavior.

are not necessarily driven out of the market. Instead, as shown previously, they goad other traders into speculative behavior which makes everyone end up with similar profits. While this suggests that a lack of self-control capabilities is not necessarily detrimental to trading performance, it shows how negative the effect can be for markets, when other traders imitate their behavior.

5.4 Evidence on Psychological Channels

There are some indicators that the influence of the fast and impulsive system 1 on decision making has increased, while the slow and deliberative system 2 seems to affect trading less, which is in the spirit of dual systems perspectives of decision making (Kahneman, 2011).

First we consider system 1 by looking at measures of experienced emotions during the market. We collected these in the questionnaires at the end of half of the *MIXED* sessions. Then we turn to system 2 by considering the impact of the CRT scores on trading profits.

5.4.1 Increased Emotional Reactivity

At the end of the experiments that we conducted in November 2015, we asked participants a number of questions relating to their emotional experience during the asset market.[23] In particular, we asked participants to rate how strongly they felt a number of emotions at the beginning of the first period and at the end of the last period respectively.

Table 3 reports the results from those emotions that have previously been connected to overpricing in experimental asset markets (Andrade et al., 2015; Breaban and Noussair, 2013; Hargreaves Heap and Zizzo, 2011; Lahav and Meer, 2012). Note that we collapsed all the emotional measures on the treatment group level within each market and test for differences with Wilcoxon-Signed Rank tests. Strikingly, every single measure of experienced emotions is higher in the *MIXLO* than in the *MIXHI* group, with many measures being statistically significant. At the beginning of period 1, *MIXLO* participants report to feel borderline significantly more surprise ($p = 0.103$) and significantly more joy ($p = 0.058$). Remember that Lahav and Meer (2012) found that inducing positive mood before the market stage leads to higher deviations from fundamental values and thus larger overpricing and that correlational studies also suggest such a relationship (Breaban and Noussair, 2013; Hargreaves Heap and Zizzo, 2011). Furthermore, at the end of the trading period, *MIXLO* participant report significantly higher levels of excitement, fear and surprise than *MIXHI* participants (all $p < 0.05$).

We also asked participants explicitly how strongly their behavior was driven by emotions and how much they had tried to suppress the influence of emotions on their trading behavior. Even

[23] We also provided participants with a questionnaire regarding their trading behavior which we do not report. The average responses to all the emotion-related questions and the respective test statistics can be found in Table 8 of the appendix. Changes in emotions between the two points in time can be found in Table 9.

though the effects go in the expected direction given the responses to the questions on experienced emotions, they fail to reach significance (both $p > 0.2$). These results indicate that the behavior of the participants with reduced self-control might have been driven by emotional factors to a larger degree than they were aware of.

	MIXHI	MIXLO	p-value
Beginning of the first Period			
excitement	4.200	4.500	0.400
fear	2.100	2.175	0.395
surprise	3.600	4.050	0.103
joy	3.625	4.375	0.058*
End of the last Period			
excitement	3.425	4.200	0.042**
fear	1.900	2.575	0.014**
surprise	2.450	3.400	0.030**
joy	3.375	4.125	0.207
Self-Evaluation of Emotional Reactivity			
emotion driven	2.475	2.725	0.362
suppressed emotions	5.300	4.950	0.205

Data collapsed on the treatment level per market; responses were on 7 point Likert scales; test results from Wilcoxon Signed Rank tests; *** p<0.01, ** p<0.05, * p<0.1

Table 3: Ex-Post Reported Emotions during the Market within *MIXED*

5.4.2 Reduced Cognitive Control

Previous research has shown that CRT scores correlate positively with individual participants' profits in similar experiments (Corgnet et al., 2014; Noussair et al., 2014). Toplak et al. (2011) find that CRT scores are correlated with measures of cognitive ability, thinking disposition and executive functioning. We therefore interpret the CRT score as a measure of cognitive control. In order to check whether the effect of the CRT on profits is similar to these studies, we ran additional regressions which we report in table 4. Note that we excluded participants who had indicated that they knew at least one of the CRT questions at the end of the experiment, since this knowledge of the CRT questions might have driven up correct CRT responses and might thus cloud any interaction effects between treatment condition and CRT scores.

In specification (1) we reproduce the finding that there was no statistically significant difference between the profits of traders in each condition. Specification (2) confirms the findings that higher CRT scores are positively related to higher overall profits for both conditions. However, when we separate this effect by treatment by including an interaction variable for the *MIXLO* dummy with the CRT score, we obtain a larger effect of the CRT score on profits for *MIXHI* traders, while for *MIXLO* traders the effect of CRT scores on profits is significantly smaller ($p < 0.05$) and in fact cannot be distinguished from zero overall (post-estimation Wald test, $p = 0.43$).

Thus, *MIXLO* subjects' trading seems to be relying less on their underlying ability for cognitive control. Together with the results indicating higher emotional reactivity, this suggests an interpretation of trading behavior of *MIXLO* participants as relatively more relying on impulsive system 1 processes than reflective system 2 processes (Kahneman, 2011).

	(1)	(2) Profit	(3)
MIXLO	1.036	1.040	4.342*
	(0.770)	(0.795)	(2.222)
CRT		1.084**	1.882***
		(0.497)	(0.621)
CE		0.473	0.867
		(0.550)	(0.768)
CRT × MIXLO			-1.660**
			(0.642)
CE × MIXLO			-1.031
			(1.125)
Constant	7.035***	5.302***	3.936***
	(0.441)	(1.097)	(1.323)
Observations	88	88	88
R^2	0.016	0.079	0.120

Participants who indicated to know at least one of the CRT questions excluded; robust standard errors clustered on the market level in parentheses; *** p<0.01, ** p<0.05, * p<0.1

Table 4: Determinants of Profits in *MIXED*

6 Discussion

There is a tendency for *MIXLO* traders to be more involved in speculative activities in period 1: they post significantly lower offers and (insignificantly) higher asks. The fact that they post bids significantly earlier supports the notion that this is related to a higher degree of impulsivity. However, the observed overpricing does not seem to be purely the result of speculative activities, there is also some evidence that behavior of traders with lowered self-control becomes more myopic, e.g. participants reported higher levels of surprise towards the end of the market. We cannot perfectly pin down what exact behavior during the market led to the observed aggregate effect on price levels, but we find it likely that it is caused by a combination of increased tendencies to speculate and at the same time an increase in myopia.

Various studies stress the relevance of pre-market emotional state for market outcomes (Hargreaves Heap and Zizzo, 2011; Lahav and Meer, 2012; Andrade et al., 2015; Breaban and Noussair, 2013). Lahav and Meer (2012) and Andrade et al. (2015) found that positivity and excitement respectively induce more pronounced overpricing in experimental asset markets. Due to these findings, initial differences before the beginning of the asset market are one channel via which reduced self-control could have affected overpricing. Apart from the pre-market emotional state, differential emotional reactions during the market could be driving our results. Mood regulation has been shown to draw on self-control resources (Baumeister et al., 1998; Hagger et al., 2010). Therefore, it is possible that either differential emotional responses or more reactions towards emotional responses, i.e. more impulsive behavior, occurred in treated participants.

Results from the questionnaire questions we obtained from our last four sessions indicated that participants displayed more intensive emotional states in particular at the end of the asset market. Even though our experimental design does not allow us to fully rule out a direct effect of the self-control manipulation on emotional states before the asset market, given the results in previous studies of no effect of such manipulations on affect (Baumeister et al., 1998; Bruyneel et al., 2006; Hagger et al., 2010) the interpretation of the Stroop task resulting in initial differences in emotional states seems unlikely. We thus interpret the results on differing emotional states as the result of an increased sensitivity towards emotions triggered by the self-control manipulation. This is supported by the findings of more pronounced differences towards the end of the market stage, as participants whose self-control was reduced reacted more emotionally within the markets. Meanwhile, the insignificant differences in survey responses with respect to emotion regulation indicate that they were not fully aware of this.

Our effect is in line with the literature on self-control depletion. For example, Bruyneel et al. (2006) have shown that people whose self-control has been reduced rely more on affective and less on cognitive features for product choice. Similarly, it could be the case in our setting that traders with low self-control rely more heavily on affective features of the stock, e.g. the thrill from its recent price increase or from speculation, than on cognitive features, e.g. the knowledge that the fundamental value of the stock is decreasing. Thus emotional responses could be responsible for both myopic decision making or more speculative trading.

Cognitive abilities could have been affected by our treatment and thus have an impact on mispricing. Schmeichel et al. (2003) found that self-control reducing tasks negatively impact information processing such as logic and reasoning, but not the access to previously acquired knowledge. It has previously been shown that both risk aversion and impatience vary systematically with cognitive ability (Dohmen et al., 2010; Benjamin et al., 2013) which is also true for CRT scores (Frederick, 2005). Bosch-Rosa et al. (2015) observed the typical overpricing patterns only in experimental markets populated by subjects with low cognitive sophistication.[24] It is important to point out that the CRT is not a pure measure of cognitive abilities. Toplak et al. (2011) find that CRT scores are correlated with measures of cognitive ability, thinking disposition – in particular reflectivity – and executive functioning. However, in their sample predictive power of the CRT for rational thought, i.e. performance in heuristics-and-biases tasks, goes beyond the predictive power of measures of cognitive abilities, measures of thinking disposition or measures of executive processing. They conclude that "(...) the CRT is a measure of the class of reasoning error that derives from miserly processing." (Toplak et al., 2011, p. 1284). In our sample, we found no effect of the difficult version of the Stroop task on the CRT. This might be because the incentives to do well are relatively high and people can temporarily overcome self-control problems if the motivation is sufficient (Muraven and Slessareva, 2003; Vohs et al., 2012), which given a similar zero effect on non-incentivized CRT scores (Lucks, 2015) seems unlikely. However, there is evidence that there has been an effect of self-control depletion on cognitive abilities in our data: In the regressions in Table 4, similar to Corgnet et al. (2014) and Noussair et al. (2014), we find that the CRT carries predictive power for traders' profits, but only if their self-control has not been previously reduced. It seems therefore that for traders low in self-control the predictive power of the CRT is lower and cannot be statistically distinguished from zero. Thus, even though the CRT itself might not be affected by low self-control, its effect on profits seems to be disrupted. In other words, low self-control possibly reduces the availability of the cognitive resources during the trading task, while its (incentivized) measurement remains unimpaired.

7 Conclusion

In this paper, we provided causal empirical evidence for the notion that a lack of self-control can fuel overpricing and have a detrimental impact on trading behavior. To avoid confounds, we consider the experimental continuous double auction markets where Smith et al. (1988) first reported a tendency for overpricing. We exogenously reduced market paricipants' ability to exert self-control using a hard version of the Stroop task, which has previously been shown to reduce people's ability to exert self-control in subsequent tasks (Baumeister et al., 1998). Comparing two market settings where either everyone's or noone's self-control was reduced, we observe significantly more mispricing and even more overpricing as the result of low self-control capacities. When investigating the channel through which lower self-control impacts prices, we do not find support for the idea that potential

[24]Cognitive sophistication is based on CRT scores and scores from three other tasks.

changes in cognitive skills or risk preferences are not responsible for the additional overpricing. Using additional measures we also exclude fatigue as a potential channel. In order to test the robustness of our results and to determine possible differences in behavior responsible for our findings, we ran additional sessions, where only half the participants' self-control was reduced. The results from these sessions indicate that already a moderate share of participants with lowered self-control capabilities is sufficient to create overpricing of the same magnitude as in markets, where everyone's self-control was reduced. We find that speculative behavior of participants with low self-control at the beginning of the market could be driving these results, as participants place significantly lower bids and have a tendency to ask at higher prices. Furthermore, we observe no performance difference between traders with low self-control and with normal self-control on average, suggesting that low self-control traders might not be driven out of the market, but rather incite other traders to engage in speculative trading. Also, in a subset of markets where we asked participants to rate their emotional state during the market, we found that treated participants display higher levels of emotions that have been associated with overpricing at the beginning of the market. We also found more pronounced differences in emotional states at the end of the market indicating a higher degree of emotional reactivity of traders low in self-control. Additionally, we find that our measure for cognitive skills loses predictive power for profits of low self-control traders. This might indicate that even though cognitive skills seem unaffected by our treatment, different cognitive processes play a role in traders with low self-control. The results on the cognitive channels are in line with a dual systems perspective of self-control: treated participants seem to have acted more on the basis of emotions and less on the basis of cognition, thus driving up prices.

Our findings have important implications: First, with differences in self-control levels, we add a possible explanation to the large heterogeneity in overpricing present in asset market experiments. We have shown that already a moderate number of participants with low self-control are enough to nearly double overpricing. Considering that the stroop task in the first stage of the experiment only lasted five minutes, this is quite a considerable impact. Second, our results can be regarded as indicative of the role of self-control in real world markets – here both temporary reductions in self-control as well as the personality trait self-control might play an important role. Self-control might also be an important attribute on which individuals self-select into asset markets. Low self-control traders might however not be as easily exploited by high self-control traders, as one would think. Several practical implications of our results for real-world investing and trading activities come to mind. Given our findings, investment decisions should not be taken under limited self-control or willpower conditions. For instance, cognitive load, food or sleep deprivation, and self-control effort in unrelated domains have been shown to be correlated with limited self-control abilities. If such conditions are unavoidable, decision aides to sustain self-control such as commitment devices should prove useful to circumvent the potentially negative market-wide effects of low self-control trading. As a regulatory measure, cooling-off periods before buying and selling could be helpful in certain environments, but they obviously have detrimental effects in fast-paced markets.

Finally, our experiment opens up further interesting paths for research: First of all, it would be interesting to what extent our results are robust to changes in both market mechanisms, such as a call market, as well as to changes in the fundamental value process, such as a constant fundamental value process which has been shown to reduce overpricing in Kirchler et al. (2012). Finally, the role of self-control for traders in real markets remains largely unexplored.

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A Appendix

A.1 Period-specific Price Comparisons

Looking at single periods, it is possible to get a more precise picture of when the price differences between conditions arise. Table 5 reports the per-period differences of volume-adjusted mean prices, trade-adjusted mean prices, RAD and RD between *LOWSC* and *HIGHSC*. The z-values from Mann-Whitney tests testing the equality of the respective measures across the two conditions are displayed in parentheses with the respective significance level indicated by asterisks. While in the first periods we see almost no price differences, starting from period five, markets in *LOWSC* exhibit significantly higher mean prices, mispricing, and overpricing, with the peak in period 8. There are no significant differences between the two conditions in the ultimate period. By definition, this implies a more pronounced bubble and burst pattern in *LOWSC* markets than in *HIGHSC* markets.

Period	Δvolume-adjusted mean price	Δtrade-adjusted mean price	ΔRAD	ΔRD
1	-0.67	-0.85	0.0143	-0.0245
	(0.84)	(0.735)	(-0.63)	(0.84)
2	0.73	2.87	-0.0749	0.0266
	(0.105)	(-0.21)	(0.21)	(0.105)
3	4.53	3.38	0.0006	0.1646
	(-0.84)	(-0.525)	(-0.105)	(-0.84)
4	7.18	7.64 *	0.1720	0.2612
	(-1.47)	(-1.89)	(-1.26)	(-1.47)
5	9.24 *	9.03 *	0.2523	0.3359 *
	(-1.785)	(-1.785)	(-1.47)	(-1.785)
6	12.27 **	12.01 **	0.4186 **	0.4461 **
	(-2.205)	(-2.31)	(-2.205)	(-2.205)
7	15.90 **	15.84 **	0.5703 **	0.5781 **
	(-2.521)	(-2.415)	(-2.521)	(-2.521)
8	18.40 **	19.00 **	0.6573 **	0.6693 **
	(-2.521)	(-2.521)	(-2.521)	(-2.521)
9	11.69 **	11.78 **	0.4249 **	0.4249 **
	(-2.1)	(-1.995)	(-2.1)	(-2.1)
10	6.13	6.48	0.2007	0.2228
	(-1.26)	(-1.26)	(-1.05)	(-1.26)

Differences between *LOWSC* and *HIGHSC* and z-values (in parentheses) for Mann-Whitney tests. Volume-adjusted mean prices denote the average price per asset, while trade-adjusted mean prices denote average price per trade.

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

Table 5: Period-specific Effects

A.2 Additional Regression Results

	(1)	(2)	(3)	(4)
	average quantity traded			
LOWSC	-1.636	-1.643	-3.030	-3.019
	(1.646)	(1.666)	(3.551)	(3.658)
CRT		0.0705	-0.00550	0.000201
		(0.566)	(0.979)	(1.010)
CE		-0.0157	-0.248	-0.245
		(0.752)	(0.813)	(0.839)
CRT × LOWSC			0.118	0.119
			(1.172)	(1.173)
CE × LOWSC			0.581	0.576
			(1.605)	(1.658)
female				0.0667
				(1.479)
Constant	13.02***	12.98***	13.57***	13.51***
	(0.750)	(1.674)	(1.454)	(2.318)
Observations	160	160	160	160
R^2	0.012	0.012	0.013	0.013

OLS regression, dependent variable is individual average number of trades. LOWSC is a dummy where 1 stands for *LOWSC* and 0 for *HIGHSC*. CE is an individual's certainty equivalent. CRT denotes the number of correct answers on the CRT. Heteroskedasticity robust standard errors clustered at market level in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Table 6: Determinants of Trading Activity

	(1)	(2)	(3)	(4)	(5)
			average quantity traded		
MIXEDLO	-2.230	-2.049	-2.343	-1.548	-1.259
	(1.606)	(2.620)	(1.644)	(2.686)	(4.213)
RD	2.234	2.445	1.240	2.110	2.334
	(3.427)	(5.882)	(3.733)	(6.000)	(6.111)
RD × MIXEDLO		-0.421		-1.863	-2.997
		(5.362)		(5.428)	(5.744)
CRT			-0.731	-0.776	-0.217
			(0.600)	(0.553)	(0.869)
CE			1.522**	1.617**	1.332
			(0.677)	(0.719)	(0.894)
CRT × MIXEDLO					-1.217
					(1.534)
CE × MIXEDLO					0.752
					(1.546)
Constant	12.27***	12.18***	10.41***	9.891***	9.749***
	(1.850)	(2.648)	(1.653)	(2.952)	(3.120)
Observations	160	160	160	160	160
R^2	0.027	0.027	0.046	0.047	0.052

OLS regression, dependent variable is individual average number of trades. MIXLO is a dummy where 1 stands for *MIXLO* and 0 for *MIXHI*. CE is an individual's certainty equivalent. CRT denotes the number of correct answers on the CRT. Heteroskedasticity robust standard errors clustered at market level in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Table 7: Determinants of Trading Activity (MIXED)

	MIXHI	MIXLO	p-value
excitement1	4.200	4.500	0.400
fear1	2.100	2.175	0.395
surprise1	3.600	4.050	0.103
anger1	1.800	2.025	0.440
relief1	2.825	3.250	0.161
sadness1	1.525	1.725	0.324
joy1	3.625	4.375	0.058*
excitement2	3.425	4.200	0.042**
fear2	1.900	2.575	0.014**
surprise2	2.450	3.400	0.030**
anger2	2.025	2.000	0.723
relief2	3.275	4.150	0.233
sadness2	1.950	1.725	0.622
joy2	3.375	4.125	0.207
emotion intensity	2.720	3.163	0.025**
emotion valence	1.464	1.969	0.208
emotion intensity1	2.811	3.157	0.123
emotion valence1	1.754	2.069	0.123
emotion intensity2	2.629	3.168	0.025**
emotion valence2	1.604	1.944	0.400

Note: p-values from Wilcoxon-Signed Rank tests collapsing data on the market level by *MIXEDLO* and *MIXEDHI* respectively; emotion intensity is the average score over all emotion questions, emotion valence is the average score over all positive emotions minus the negative score over all negative emotions; variables ending in 1 or 2 relate to questions relating to the beginning or the end of the stock market respectively; *** p<0.01, ** p<0.05, * p<0.1

Table 8: Ratings of Emotions in MIXED Markets

	MIXHI	MIXLO	p-value
diff excitement	-0.775	-0.300	0.232
diff fear	-0.200	0.400	0.029**
diff surprise	-1.150	-0.650	0.288
diff anger	0.225	-0.025	0.575
diff relief	0.450	0.900	0.441
diff sadness	0.425	0.000	0.290
diff joy	-0.250	-0.250	1.000

Note: p-values from Wilcoxon-Signed Rank tests collapsing data on the market level by *MIXEDLO* and *MIXEDHI* respectively; *** p<0.01, ** p<0.05, * p<0.1

Table 9: Changes of ex-post Emotion Ratings in MIXED Markets

	(1)	(2)	(3)	(4)
		$IndRD_{sales}$		
LOWSC	0.326**	0.326**	0.596**	0.607**
	(0.147)	(0.147)	(0.230)	(0.218)
CRT		-0.00262	-0.0346	-0.0290
		(0.0289)	(0.0431)	(0.0437)
CE		0.0121	0.0745	0.0773
		(0.0459)	(0.0526)	(0.0535)
CRT × *LOWSC*			0.0620	0.0630
			(0.0557)	(0.0550)
CE × *LOWSC*			-0.156*	-0.160*
			(0.0841)	(0.0810)
Female				0.0655
				(0.0472)
Constant	0.193*	0.169	0.0654	0.00916
	(0.103)	(0.128)	(0.0850)	(0.0939)
Observations	160	160	160	160
R^2	0.188	0.188	0.216	0.222

OLS regression, dependent variable is Individual Relative Deviation (IndRD) for sales, an individual equivalent to market level Relative Deviation (RD) restricted to sales only. *LOWSC* is a dummy where 1 stands for *LOWSC* and 0 for *HIGHSC*. CE is an individual's certainty equivalent. CRT denotes the number of correct answers on the CRT. Heteroskedasticity robust standard errors clustered at market level in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Table 10: Determinants of individual RD based on sales

	(1)	(2)	(3)	(4)
			IndRD	
LOWSC	0.357**	0.361**	0.760***	0.771***
	(0.137)	(0.134)	(0.150)	(0.138)
CRT		-0.0448*	-0.0614	-0.0557
		(0.0244)	(0.0361)	(0.0353)
CE		-0.00420	0.0768	0.0796
		(0.0445)	(0.0511)	(0.0510)
CRT × *LOWSC*			0.0361	0.0370
			(0.0465)	(0.0455)
CE × *LOWSC*			-0.202***	-0.207***
			(0.0674)	(0.0646)
Female				0.0665*
				(0.0366)
Constant	0.121	0.177	0.0160	-0.0411
	(0.0879)	(0.109)	(0.0651)	(0.0672)
Observations	160	160	160	160
R^2	0.265	0.282	0.330	0.338

OLS regression, dependent variable is Individual Relative Deviation (IndRD), an individual equivalent to market level Relative Deviation (RD). *LOWSC* is a dummy where 1 stands for *LOWSC* and 0 for *HIGHSC*. CE is an individual's certainty equivalent. CRT denotes the number of correct answers on the CRT. Heteroskedasticity robust standard errors clustered at market level in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Table 11: Correlates of Individual Miscpricing

	(1)	(2)	(3)	(4)	(5)
			Trading Profits		
MIXLO	0.204	0.760	0.153	0.527	3.404**
	(0.443)	(0.522)	(0.392)	(0.488)	(1.525)
RD		0.660	0.768**	1.178	1.357*
		(0.721)	(0.298)	(0.676)	(0.734)
RD × MIXLO		-1.293		-0.877	-1.249
		(1.436)		(1.360)	(1.426)
CRT			1.376***	1.355***	1.834***
			(0.239)	(0.241)	(0.395)
CE			0.423	0.468	0.844
			(0.486)	(0.483)	(0.577)
CRT × MIXLO					-0.975
					(0.632)
CE × MIXLO					-0.774
					(0.867)
Constant	-0.101	-0.384	-2.846**	-3.089**	-4.474***
	(0.223)	(0.261)	(1.025)	(1.054)	(1.209)
Observations	160	160	160	160	160
R^2	0.001	0.005	0.156	0.158	0.184

OLS regression, dependent variable is average trading profit from asset market in € , RD is the average Relative Deviation in a market, RD$\times LOWSC$ is the interaction of RD and a dummy that equals one, if the subject is assigned to the hard version of the Stroop task. CRT denotes the number of correct answers in the CRT, CE is the individual certainty equivalent, robust standard errors clustered on market level in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Table 12: Determinants of Trading Profits

A.3 First Period Behavior as a Predictor for Overpricing

	ρ	p-value
$\overline{p_{bid}}$	0.338	0.218
$\overline{p_{ask}}$	0.341	0.196
$\overline{q_{bid}}$	0.575	0.025**
$\overline{q_{ask}}$	-0.271	0.311
$\overline{time_{bid}}$	0.686	0.005***
$\overline{time_{ask}}$	-0.376	0.151
$\overline{firsttime_{bid}}$	0.486	0.066*
$\overline{firsttime_{ask}}$	-0.076	0.778

Rank correlations of average first-period behavior over all market participants with average relative deviation for *MIXED* markets, *** p<0.01, ** p<0.05, * p<0.1

Table 13: Rank Correlations of First Period Behavior with Overpricing

A.4 Distribution of Answers in the Stroop Task

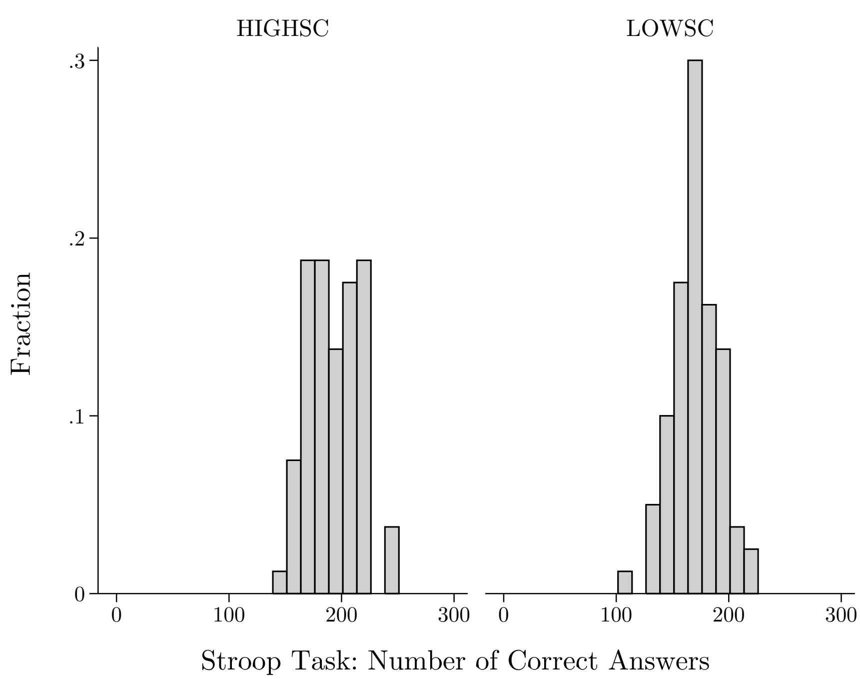


Figure 7: Correct Stroop responses in *HIGHSC* vs. *LOWSC*

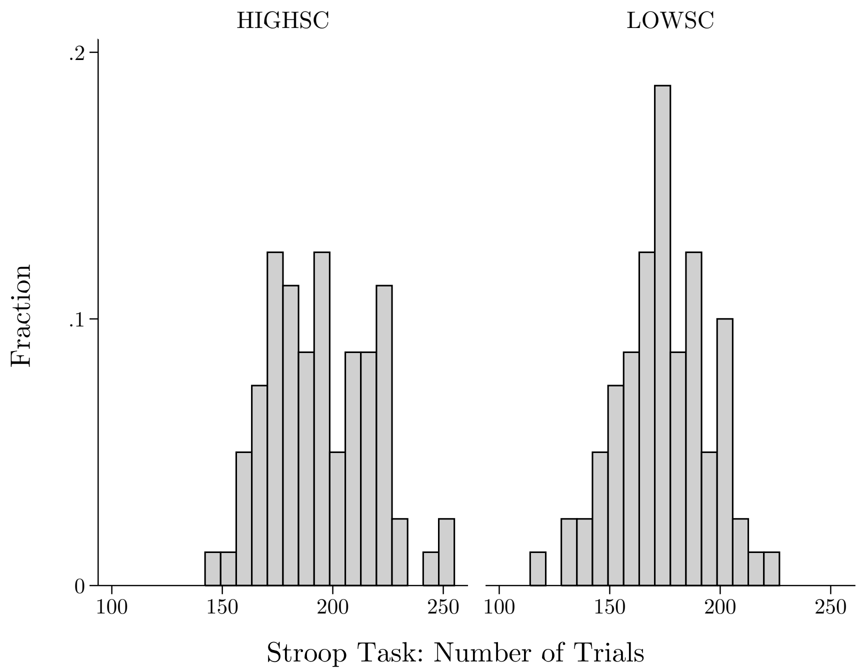


Figure 8: Stroop trials in *HIGHSC* vs. *LOWSC*

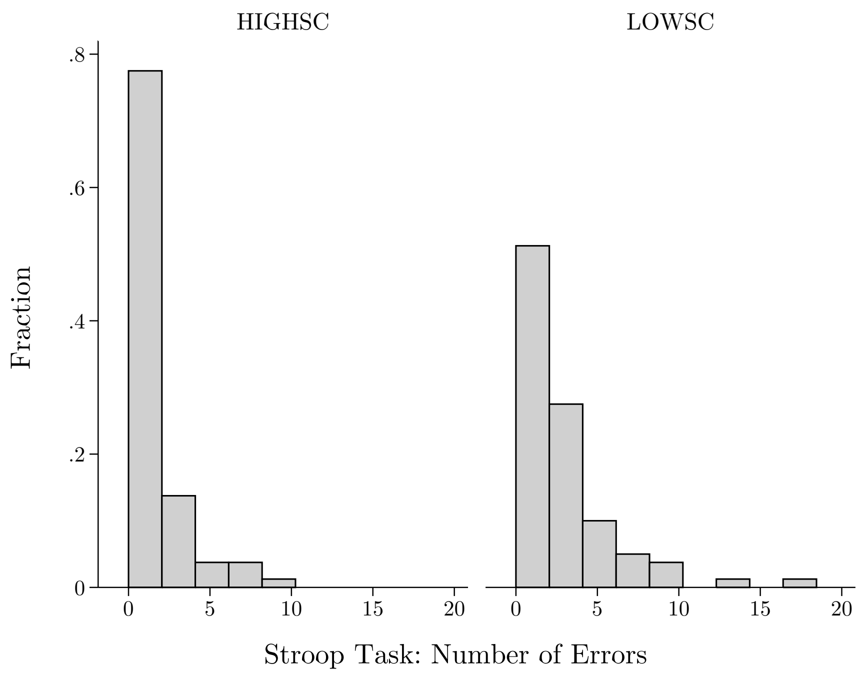


Figure 9: Errors in the Stroop task in *HIGHSC* vs. *LOWSC*

Distribution of Answers in the Stroop Task

HIGHSC	mean	standard deviation
Correct Answers	192.65	22.6146
Trials	194.55	23.55973
Errors	1.9	1.879941
LOWSC	**mean**	**standard deviation**
Correct Answers	171.3125	20.68363
Trials	174.45	20.96948
Errors	3.14	2.971356

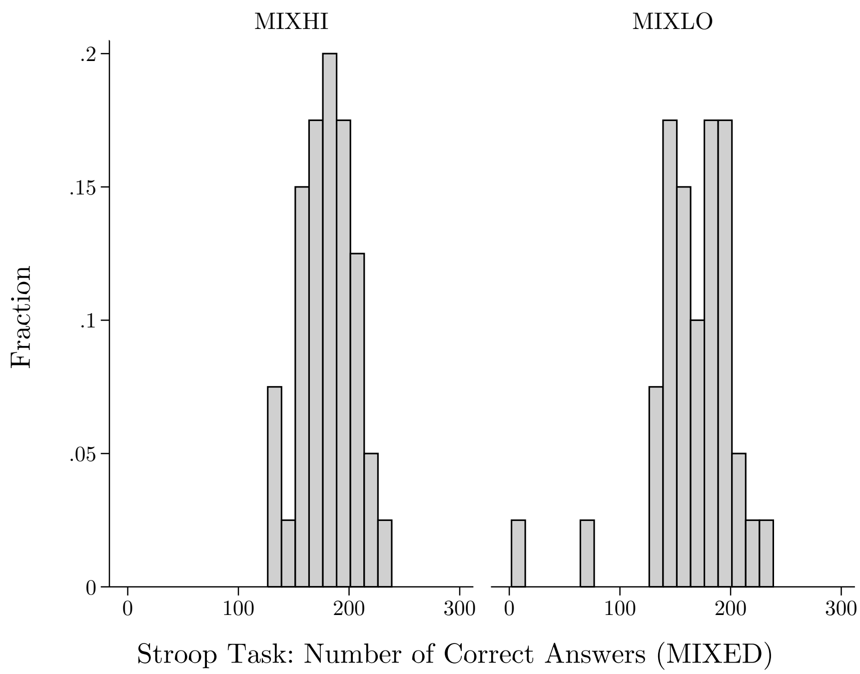


Figure 10: Correct Stroop responses in treatment *MIXED* by condition

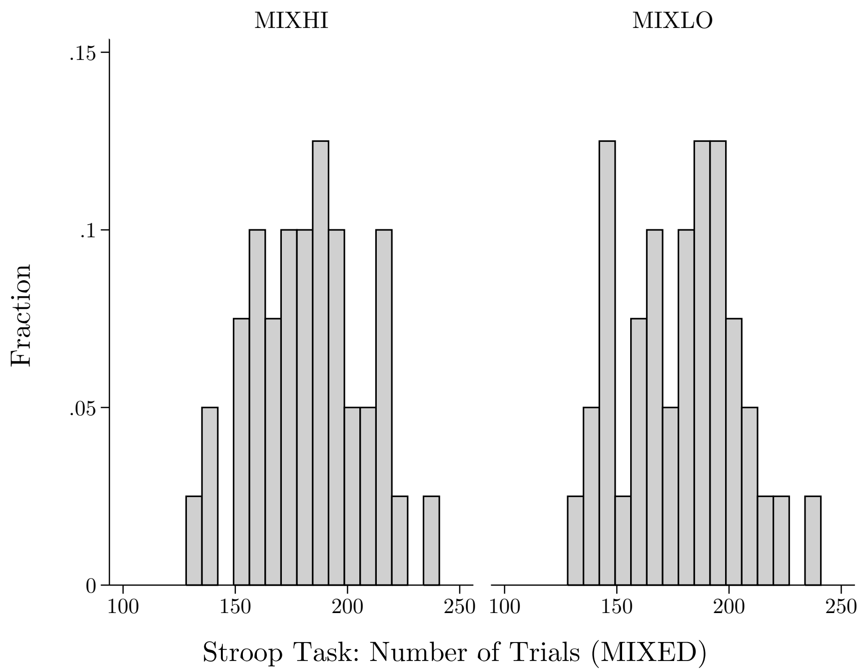


Figure 11: Stroop trials in treatment *MIXED* by condition

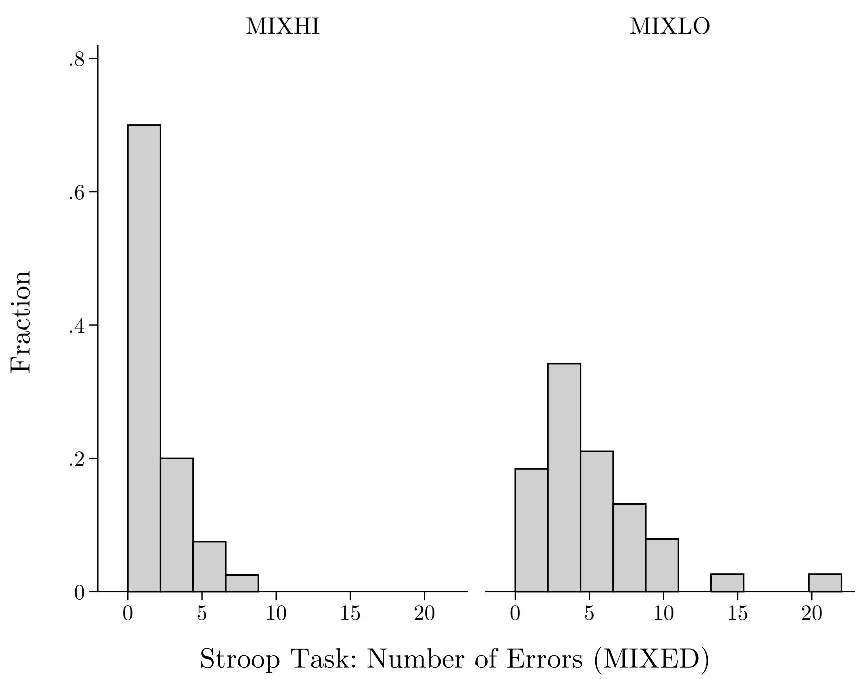


Figure 12: Errors in the Stroop task in treatment *MIXED* by condition[25]

Distribution of Answers in the Stroop Task (MIXED)

HIGHSC	mean	standard deviation
Correct Answers	179.225	24.1135
Trials	182.65	24.59784
Errors	2.425	1.448031
LOWSC	**mean**	**standard deviation**
Correct Answers	164.05	39.93838
Trials	178.3	25.47518
Errors	13.25	36.44367

A.5 Distribution of Subjective Measures

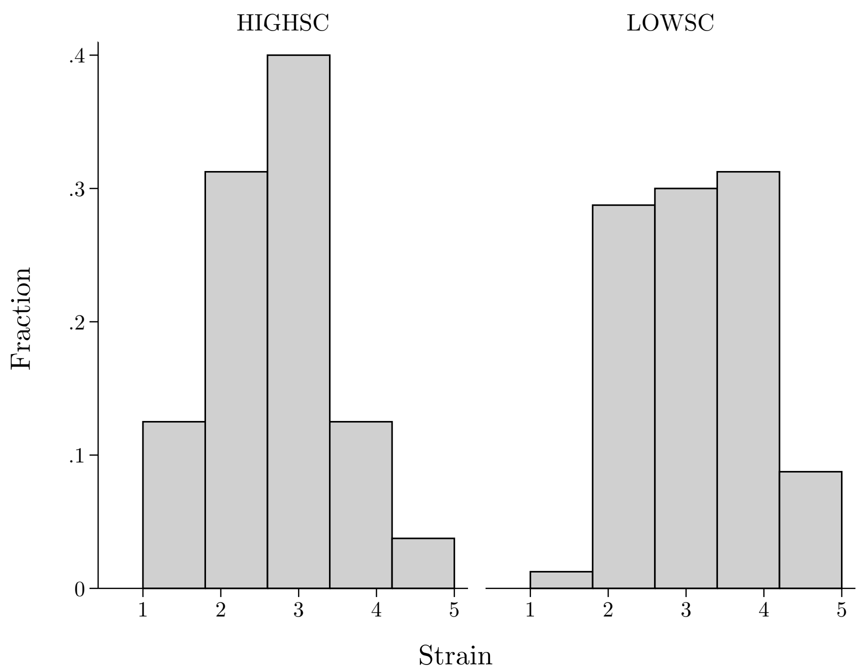


Figure 13: Strain in *HIGHSC* vs. *LOWSC*

[25]Two outliers were dropped from this display in the LOWSC group, both of whom apparently did not fully understand the treatment. One had 123 errors and the other had 205 errors.

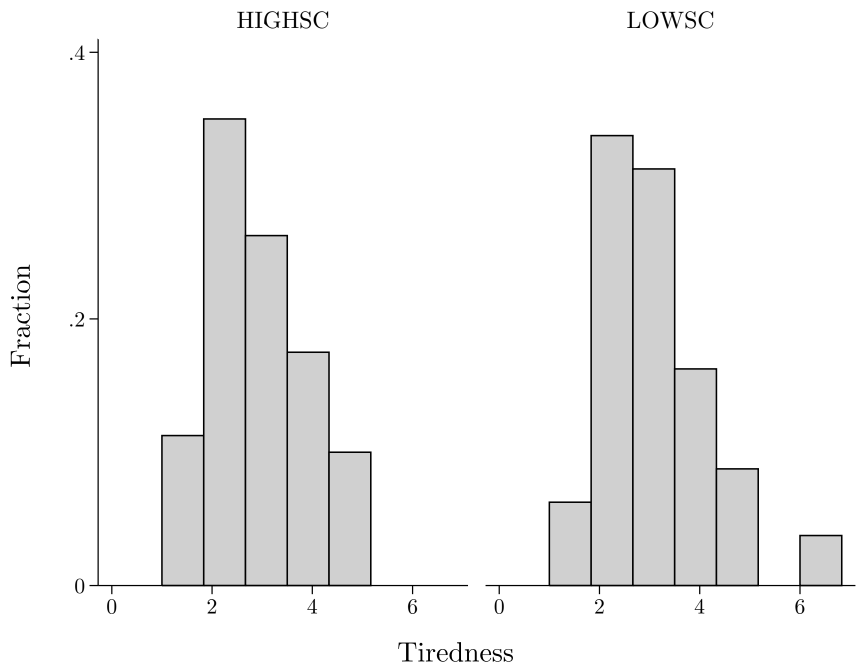


Figure 14: Tiredness in *HIGHSC* vs. *LOWSC*

Distribution of Subjective Measures

HIGHSC	mean	standard deviation
Strain	2.6375	0.9839696
Tiredness	2.8	1.162712

LOWSC	mean	standard deviation
Strain	3.175	0.9907803
Tiredness	2.9875	1.206457

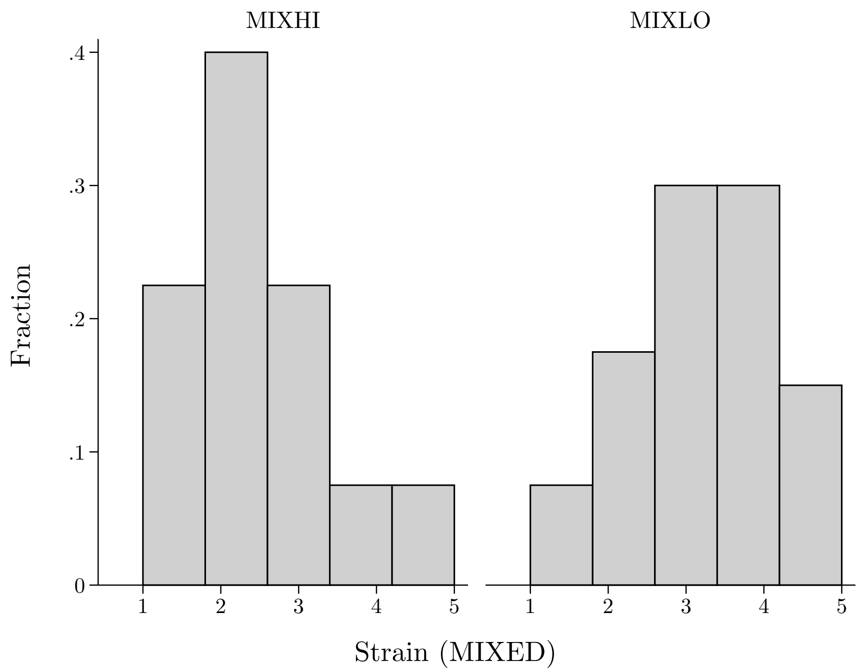


Figure 15: Strain in treatment *MIXED* by condition

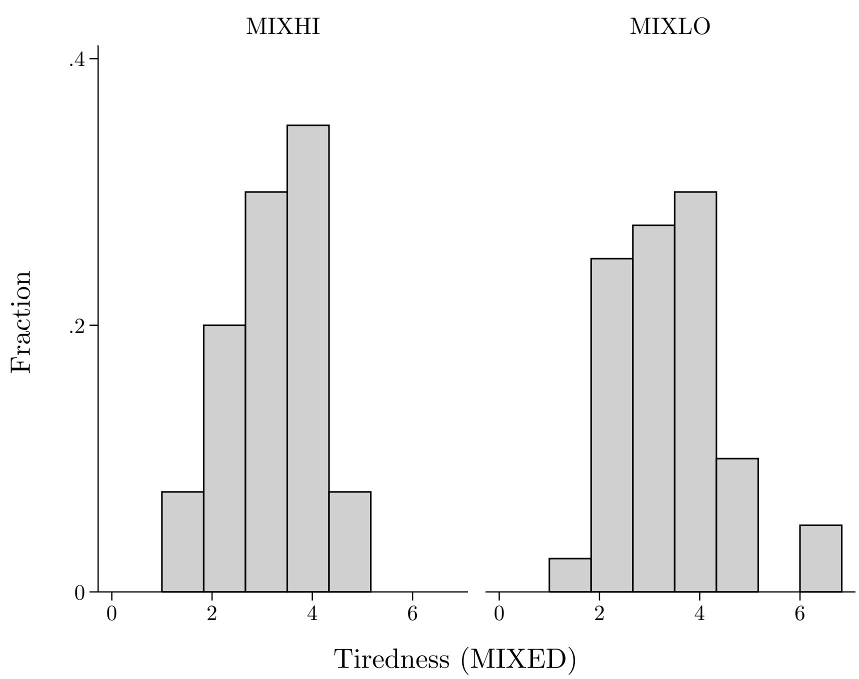
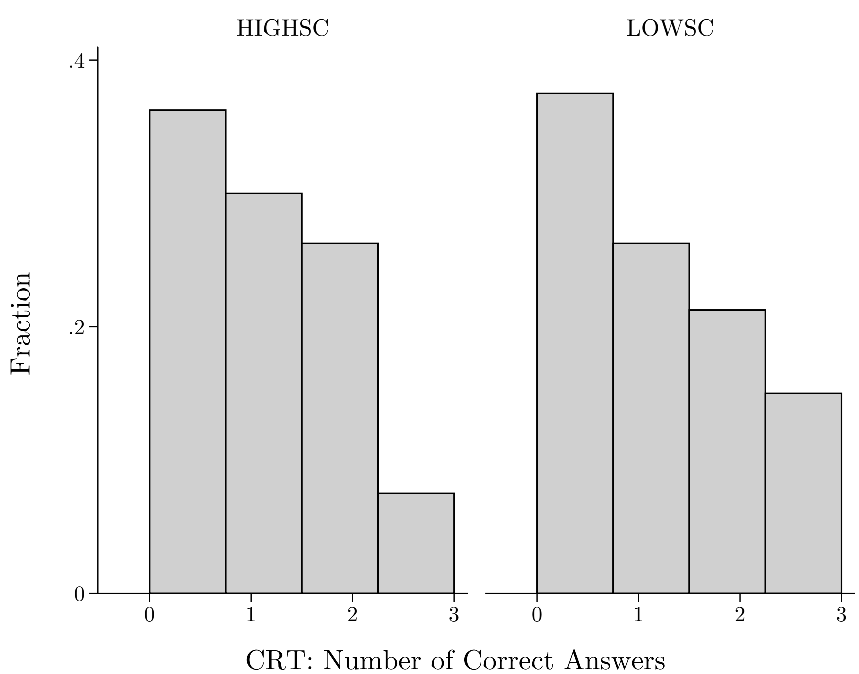


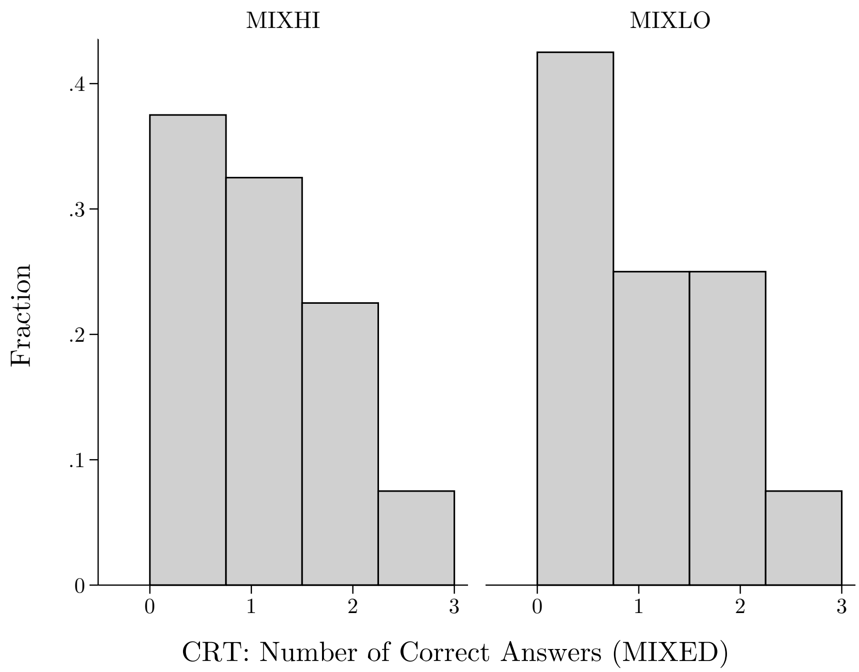
Figure 16: Tiredness in treatment *MIXED* by condition

Distribution of Subjective Measures (MIXED)

MIXHI	mean	standard deviation
Strain	2.375	1.14774
Tiredness	3.15	1.075365
MIXLO	**mean**	**standard deviation**
Strain	3.275	1.154423
Tiredness	3.35	1.188621

A.6 Distribution of Answers in the Cognitive Reflection Task

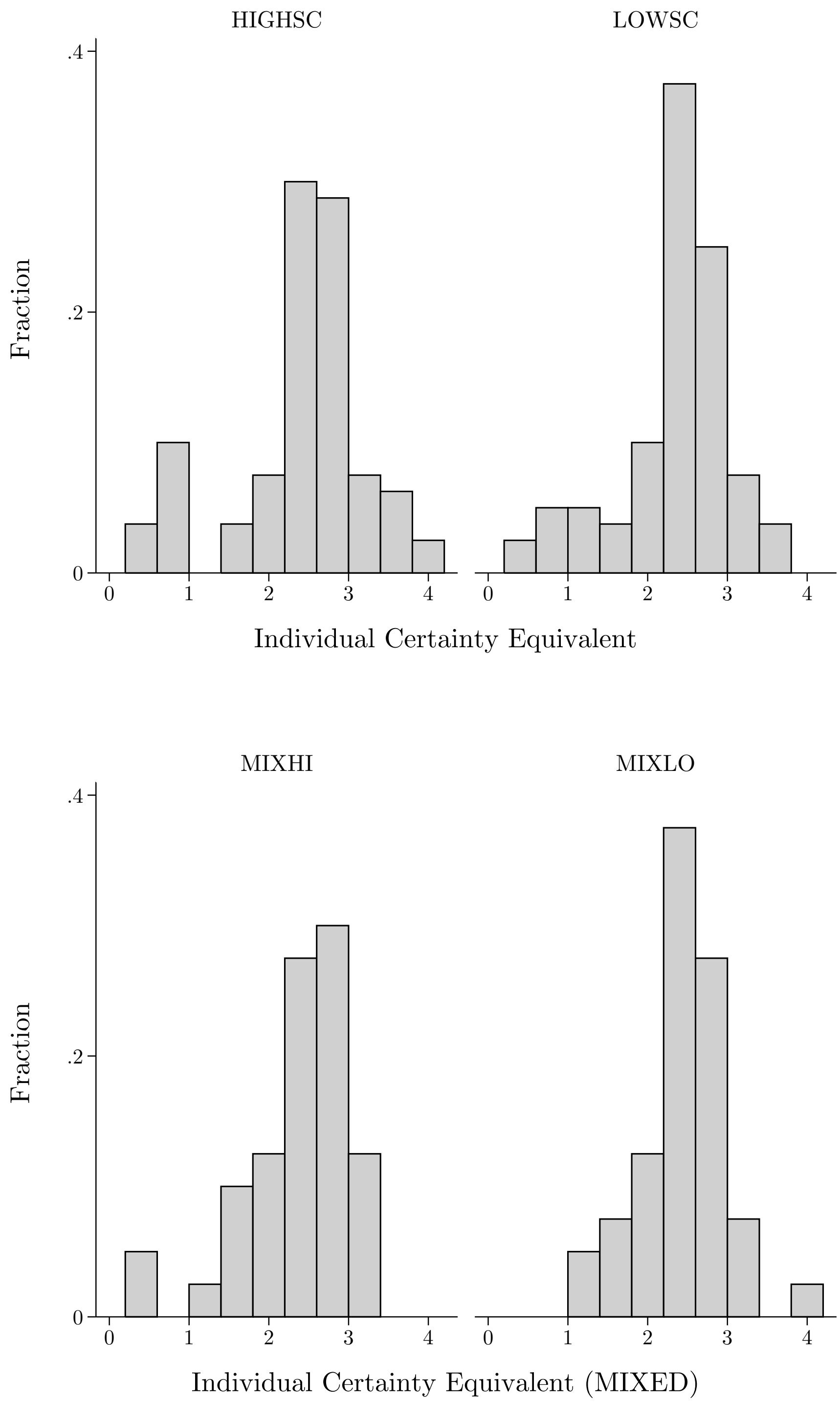




Distribution of Answers in the Cognitive Reflection Task

	mean	standard deviation
HIGHSC	1.05	.9665284
LOWSC	1.1375	1.087836
MIXED	mean	standard deviation
MIXHI	1	.9607689
MIXLO	.975	.9996794

A.7 Distribution of Certainty Equivalents



Distribution of Individual Certainty Equivalents

	mean	standard deviation
HIGHSC	2.2	.8467361
LOWSC	2.145	.6964467
MIXED	mean	standard deviation
MIXHI	2.16	.6766433
MIXLO	2.24	.5494986

A.8 Instructions

Welcome to the experiment and thank you for your participation!

Please do not talk to other participants of the experiment from now on

General information on the procedure

The purpose of this experiment is to investigate economic decision making. You can earn money during the experiment, which will be paid to you individually and in cash after the experiment has ended.

The whole experiment takes about 1.5 hours and consists of 3 parts. At the beginning you will receive detailed instructions for all parts of the experiment. If you have any questions after reading the instructions or at any time during the experiment please raise your hand. One of the experimenters will then come to you and answer your question in private.

During the experiment, you and the other participants will be asked to make decisions. In some parts, you will interact with other participants. Thus both your own decisions and the decisions of other participants can determine your payoffs. Your payoffs are determined according to the rules which are explained in the following. As long as you can make your decisions, a countdown will be displayed in the upper right corner of the screen which is intended to give you an orientation for how much time you should use to make your choices. In most parts you can exceed the time limit if needed; in some parts, however, you can only act within the time limit (You will be informed about this beforehand). Information screens not requiring any decisions will disappear after the time-out.

Payment

In some parts of the experiment we will not refer points instead of Euros. Points will be converted to Euros at the end of the experiment. You will be informed about the exchange rate at the beginning of the respective part.

For your timely arrival you will receive 4 € additionally to the income earned during the experiment.

Anonymity

We evaluate the data from the experiment only in aggregate and never connect personal information to data from the experiment. At the end of the experiment you have to sign a receipt, which we need for our sponsor. The sponsor does not receive any further data from the experiment.

Aid

On your desk you will find a pen. Please leave it on there after the experiment.

Part I

Task

The first part of the experiment consists of a task that will last 5 minutes. You will see a black screen on which words in different colors will appear. Here you can see an example:

You will be asked to click one of the buttons at the bottom of the screen. You will be asked to choose the button corresponding to the color the word is written in (**not** the word itself). In the example you should click on "yellow".

After clicked a button, the screen disappears and **another word in another color** appears.

Please try to solve **as many word/color combinations** as possible within 5 minutes.

After 5 minutes the first part ends automatically and the second part begins.

Payment

You receive 3 € for part I.

Part II

Task

In the second part you first have to answer three questions. For each question answered correctly you receive 0.5 € = 50 Cents.

Afterwards, you will be shown **10 decision problems**. In each of these problems you can choose between **a lottery and a safe amount of money**. The lottery remains unchanged within a period, whereas the safe amount of money increases with every additional decision problem. As the safe amount of money is strictly increasing from row to row, you should stay with the safe amount of money after you have switched to it once.

Your decision is only valid after you have made a choice for each problem and then confirmed it by clicking the OK-button on the bottom right of the screen. Take enough time for your decisions, as your choice – as described in the following – will determine your payoff from this part.

Here you can see what your screen will look like:

Your profit will be determined according to the following rules: First, **the computer chooses randomly and with equal probability one of the ten decision problems for payment**. If you selected the lottery in the relevant problem, the computer will simulate the outcome and you will receive it as payment. If you selected the safe amount in the relevant problem, you will receive it for sure.

For example: Assume the computer randomly chooses the first decision problem and you chose the lottery. Then the computer will simulate the outcomes of this lottery and you either receive 0.2 € (50% probability) or 4.2 € (50% probability).

Payment

The sum of your payoffs from the questions answered correctly at the beginning and your payoff from the decision problem chosen by the computer are your payment for part II of the experiment. Please note: The computer will directly calculate the result. However, you will only learn about this at the end of the experiments, i.e. how many questions you answered correctly and which decision problem with which outcome the computer selected for you. That information will be presented to you on a separate screen at the end of the experiment.

After the end of part II, part III begins automatically.

Part III

Payment

In the third part of the experiment we refer to points rather than Euros. Points are converted to Euros at the end of the experiment according to the following exchange rate

500 points = 1 Euro (1 point = 0.002 Euros = 0.2 Cents)

Short Description

The third part of the experiment consists of a simulated stock market. The stock market lasts for 10 consecutive periods. Within these periods you can buy or sell shares of a single firm.

At the end of each period for every share that you own you receive either a dividend of 10 points (probability 50%) or 0 points (probability 50%).

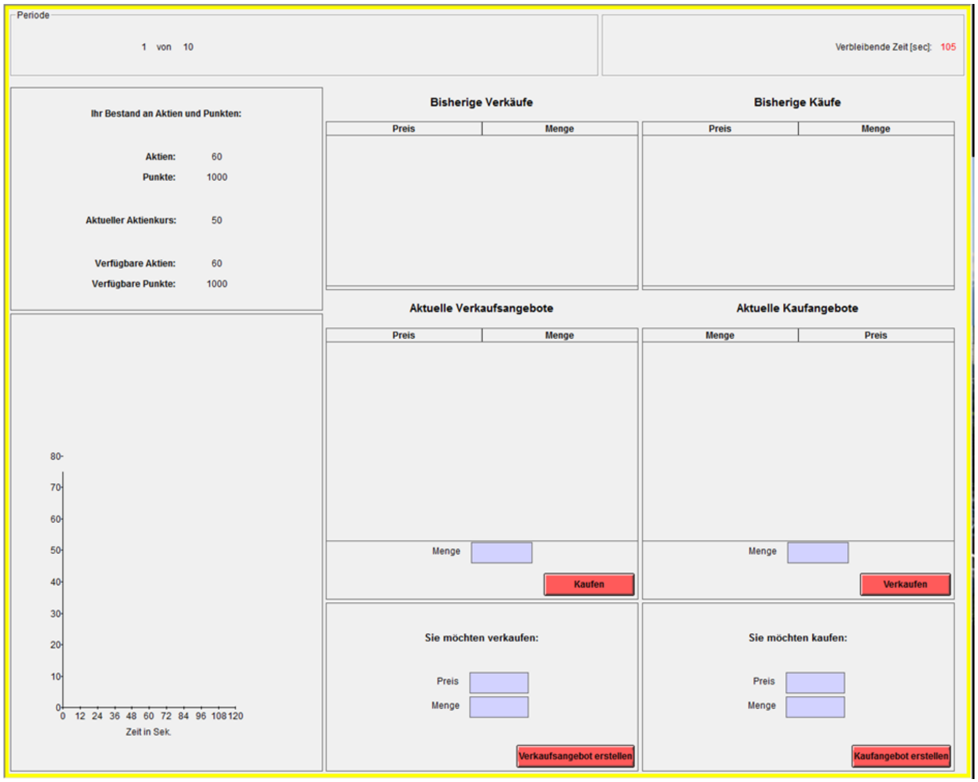
During the 2 minutes trading period you can either offer to sell or buy shares or accept existing buying or selling offers by other participants.

Detailed description: Trading Period

At the beginning of the first trading period you will receive an endowment of shares and points. Every participant receives either 20 shares and 3000 points or 60 shares and 1000 points. The distribution of endowments is random with a 50% probability of receiving each endowment.

Each period lasts exactly 120 seconds (= 2 minutes) and all screens disappear after the time out. You cannot make any trades or offers until he next trading period starts. During a trading period neither your amount of shares nor your amount of points can fall below zero.

During a trading period your screen will look like the following.



In the upper box you see the current period and how much time you have left in the current period. Below it to the left the box displays how many shares you currently own and how large your current wealth is expressed in points. Additionally the current share price and the amount of available shares and points are displayed.

Available shares are those of your shares that you have not offered for sale yet. If you offer to sell shares, you still own them, but they will be subtracted from your account as soon as someone else accepts your offer. Hence, you can only make sale offers that do not exceed your current amount of available shares.

Available points are those of your points that you have not used for buying offers yet. If you make an offer to buy shares, you still own the points, but they will be subtracted from your account as soon as someone else accepts your offer. Hence, you can only make buying offers that do not exceed your current amount of available points.

On the bottom left you can see a graph that shows the evolution of share prices in the current period. On the horizontal axis (the x-axis) you can see the time in seconds at which a trade was made. On the vertical axis (the y-axis) you can see the corresponding price.

In the upper part of the screen you see two lists that have the headlines “Previous Sales” and “Previous Purchases”. Here, every trade that you made is listed. For each trade where you bought shares, price and quantity will be listed in “Previous Purchases”. For each trade where you sold shares, price and quantity will be listed in “Previous Sales”.

Below you find two lists with the headlines “Current Selling Offers” and “Current Buying Offers”.

Accepting Selling Offers

In the list “Current Selling Offers” you find price and quantity of each offer, in which a participant offers to sell shares. Your own selling offers will also appear in this list. You can accept every offer in this list (except for your own offers) by marking the corresponding entry in the list, entering the quantity you want to buy into the field “quantity”, and then confirming by clicking on the button “Buy”. If you accept a selling offer, you will receive the number of shares that you have entered from the seller and the seller receives the corresponding price for each share he sold to you.

Please note: You can also buy less than the number of shares stated in the offer. In that case the offer of the seller will remain on display in the list after the trade, but the number of shares on offer will be reduced by your purchase. Example: A seller makes an offer to sell 10 shares at the price of 60 points each. A buyer buys 6 of those shares. Then an offer to buy 4 shares at the price of 60 points each will continue to be available to all other participants.

Please note that the computer automatically marks the best selling offer (i.e. the one with the lowest price) with a blue bar. You can recognize your own offers, as they are not displayed in black but in blue font.

Accepting offers to buy

In the list “Current Buying Offers” you find price and quantity of each offer, in which a participant offers to buy shares. Your own buying offers will also appear in this list. You can accept every offer in this list (except for you own offers) by marking the corresponding entry in the list, entering the quantity you want to sell into the field “quantity”, and then confirming by clicking on the button “Sell”. If you accept a buying offer, the other participant will receive the number of shares that you entered and you receive the corresponding price for each share you sold.

Please note: You can also sell less than the number of shares the buyer offers to buy. In that case the offer of the buyer will remain on display in the list after the trade, but the number of shares demanded will be reduced by your sale.

Please note that the computer automatically marks the best buying offer (i.e. the one with the highest price) with a blue bar. You can recognize your own offers according to their blue font.

Creating Selling or Buying Offers

In the bottom part of the screen you have the possibility to create your own selling or buying offers. If you want to create an offer to sell, enter the quantity of shares that you want to sell and the price per share which you demand for each unit in the field below “You Want to Sell” . After clicking the button “Create Selling Offer”, your selling offer will show up in the list “Current offers to sell". Example: You want to sell 10 shares at a price of 55 points per share. Then you enter 10 into the field "Quantity" and 55 into the field "Price".

If you want to create a buying offer, enter the quantity that you want to buy in the field below "You Want to Buy" and the price per share for which you are willing to buy that quantity. After clicking the button "Make Buying Offer" your offer will show up in the list "Current Buying Offers". Example: You want to buy 20 shares at a price of 45 points per share. Then you enter 20 into the field "amount" and 45 into the field "price".

Please note: An offer to buy or to sell that has been made cannot be cancelled. Only if no one accepts an offer during the course of a trading period, it will not be displayed in the next period of trade.

Dividends

After the end of a trading period the following screen displays a summary of the previous period showing you how many shares and points you own, whether a dividend has been paid and if so, how large your overall dividend payments were.

In each period the dividend per share either amount to 10 points (with a probability of 50%) or to 0 points (with a probability of 50%) and is the same for all shares. After the end of period 10, all shares are worthless. All participants learn the realization of the dividend simultaneously on a separate screen at the end of the corresponding period.

The following table displays the value pattern of a share, i.e. the expected value of the remaining dividends. The first column indicates the current period, in the second column you find the number of remaining dividend payments. The third column shows the average expected dividend per share and period. The last column shows the average of remaining dividends per share in the corresponding period.

Current period	Remaining dividend payments	x	Average dividend value per period (0 or 10 with equal probability)	=	Average remaining dividends per share that you own
1	10		5		50
2	9		5		45
3	8		5		40
4	7		5		35
5	6		5		30
6	5		5		25
7	4		5		20
8	3		5		15
9	2		5		10
10	1		5		5

Assume for example that four trading periods remain. As the dividend per share is either 0 or 10 points with a probability of 50% each, this yields an expected dividend of 5 points per share and period. Assume you only own one single share which you intend to hold until the market closes. Then you can expect a total dividend payment for the four remaining periods of '4 remaining periods' x '5 points' = '20 points'.

Payoff

At the end of part III the shares no remaining value. Only your amount of points will be converted to Euros according to the exchange rate stated above of 1 point = 0.002 Euros = 0.2 Cents. Afterwards, you will see a screen displaying your payoffs from the second part.

In the following, we will ask you to completely and honestly answer some questions concerning your person. On leaving the laboratory, we will pay you your profit privately and in cash. Please remain seated until we call you up in a random order. Please leave the instructions and the pen at your desk and take your numbered seat card with you.

Practice Period

Before you start today's experiment with part I, you will first play a practice period of part III to become familiar with the stock market. The payoff from this practice period will not influence your final payoff. Please note that the realization of the dividend and your endowment are not necessarily identical to the first period of part III as the realization is random and endowments will be randomly assigned.

After completion of the practicing period part I of the experiment begins.