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Abstract

One explanation for overpricing on asset markets is a lack of traders' self-control. Self-control is the individual capacity to override or inhibit undesired impulses that may drive prices. We implement the first experiment to address the causal relationship between self-control abilities and systematic overpricing on financial markets. Our setup can detect some of the channels through which individual self-control restrictions could transmit into irrational exuberance in markets. Our data indicate a large direct effect of restricted self-control abilities on market overpricing. Low self-control traders report stronger emotions after 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, and we analyze how the lack of self-control abilities that are related to animal spirits is associated with emotions and trading behavior. 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 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] Similarly, anecdotal evidence from rogue traders show

[1] Source: Keynes (1936), p. 136.
[2] `http://www.businessweek.com/1999/99_27/b3636006.htm`

that they completely lost their self-control abilities at some stage. 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 evidence suggests that self-control matters for trading success on an individual level. This paper is the first to provide empirical evidence on the *causal* effect of a variation in self-control abilities on trading outcomes.[4] 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 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), although it has also been questioned lately (Carter and McCullough, 2013). While validated survey measures for *trait* self-control exist, they can only provide correlational inference.

In the spirit of Keynes we use a laboratory experiment to first investigate aggregate market outcomes and then extend our analysis to individual behavior and performance. We use a well-established 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 mispricing and, in particular, overpricing. This experimental asset market is known for its basic tendency to exhibit overpricing; it features a dividend-bearing asset with decreasing fundamental value. This setup resembles a large

[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).

[4] However, there is a quickly growing empirical literature on the effects of self-control abilities on decision making in other domains relevant to economists (see, for instance, Beshears et al. (2015)).

class of assets traded on real asset markets: options, bonds and depletable resources all exhibit a value that decreases over time.

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/depleting version and in an easy version (i.e. a placebo 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 situations outside the laboratory in which also trait self-control matters.

A drop in self-control abilities may increase the extent of overpricing on a market through a variety of channels. One psychological transmission mechanism runs through an increased influence of the impulsive decision making system. A consequence could be that trader behavior becomes more easily swayed by observing others' behaviors on the market (for instance, a more pronounced tendency to momentum trading). Another behavioral mechanism relates to an heightened influence of emotions (for instance, the excitement after seeing the prospect of making more money, or a stronger psychological reward of interim gains). Yet another option, potentially related to impulsivity, would be a stronger role of biases in decision making such as myopia, limiting the ability to correctly foresee the declining fundamental value and thus creating histories of overpricing on the market.

Our main finding is a significantly higher level of overpricing in 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 both depleted and non-depleted traders the effect is similar in size and also highly significant. Apparently, having some self-control depleted traders on a market suffices to create the additional overpricing effect. We also observe that low self-control traders do not make lower average profits than high self-control traders as the trading behaviors converge quickly. An initial tendency to bid low and early by low self-control traders can only be found in the first trading period. As traders do not earn different profits following the convergence, low self-control traders are not driven out of the market, delivering an explanation why such a bias may persist in some markets.

We then investigate potential channels through which reduced self-control affects outcomes. First, risk attitudes or cognitive abilities of traders are not affected and therefore not mediating the treatment effect. Second, self-control depleted traders do not trade significantly less than non-depleted traders, ruling out a simple exhaustion effect. Third, self-control depleted subjects report stronger emotions that are commonly associated with overpricing in asset markets. Relatedly, we find that cognitive abilities lose their predictive power for earnings when subjects are low in self-control. This suggests that self-control depleted traders become more impulsive, emotion-driven and fail to utilize some of their cognitive skills.

2 Related Literature

Our literature overview focuses 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 theoretical approaches in psychology and in economics that take self-control abilities and potential self-control problems into account.

First, self-control can straightforwardly 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.[5] 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, in connection with quasi-hyperbolic discounting) and for the fact that cognitive load makes temptations harder to resist.

Third, willpower as a depletable resource has been modeled directly in economics. Ozdenoren et al. (2012) look at a consumption smoothing model that views willpower as a depletable resource, and Masatlioglu et al. (2011) consider lottery choices.

Is there empirical evidence for self-control abilities or willpower to be indeed limited or depletable resources? Many researchers in psychology have shown that exerting self-control consumes energy and consequently diminishes the available resources for other acts that require self-control.[6] 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 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 self-control depletion. We reduce self-control abilities by exposing experimental participants to a self-control demanding task before the main task (known as the dual task paradigm). Such setups have been used in other domains in economics, mainly in

[5]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).

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

the context of individual decision making. For example, the consequences of self-control variations in decision making under risk have been studied. Several papers report increased risk aversion following self-control depletion (Unger and Stahlberg, 2011; Kostek and Ashrafioun, 2014). However, a number of studies also reveal an increase in risk taking following similar manipulations (Bruyneel et al., 2009; Freeman and Muraven, 2010; Friehe and Schildberg-Hörisch, 2017). Both Stojić et al. (2013) and Gerhardt et al. (2017) find no significant effect of self-control manipulations on risk preferences elicited from choice lists. Bucciol et al. (2011, 2013) show in field experiments with children and adults that self-control depletion leads to reduced productivity in subsequent tasks. Buckert et al. (2017) report that the Stroop task reduces prices in a Cournot game, and 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. (2016) 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.[7]

Existing studies also 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 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

[7] 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. A similar result is provided by Kocher et al. (2017).

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.[8] Trader inexperience and confusion have been considered as one of the aggravating factors of overpricing (Dufwenberg et al., 2005; Kirchler et al., 2012), and Bosch-Rosa et al. (2018) for example show that grouping traders by cognitive skills leads to increased overpricing for groups with low cognitive sophistication. Nadler et al. (2017) provide evidence that giving testosterone to a group of male participants significantly increases prices, and Petersen and Spickers (2015) find that inducing stress decreases overpricing. In line with our findings, Dickinson et al. (2017) report that sleepy traders generate more overpricing.

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. (2016) 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 more overpricing. The role of emotions in experimental asset markets has also been evaluated using self-reported emotions on Likert scales (Hargreaves Heap and Zizzo, 2011) and face reading software (Breaban and Noussair, 2018), 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.

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

3 Experimental Design

The experiment consisted of four independent main parts: (i) instructions and dry runs of the asset market without monetary consequences and without the possibility to build reputation for the parts to come; (ii) the main treatment variation in self control, the Stroop task (Stroop, 1935) in two treatment versions; (iii) elicitation of risk attitudes and cognitive abilities, both incentivized; and (iv) a fully incentivized experimental asset market.

Our identification of the effects induced by a variation in self-control abilities in market prices relies on the comparison of behavior in markets following two different versions of the Stroop task. A tough version lowered self-control abilities, whereas a placebo version should have left self-control abilities largely unaffected. We implemented a condition in which all market participants were subjected to the tough version of the Stroop task (henceforth *LOWSC* for low self-control), a condition in which all participants were subjected to the placebo version (henceforth *HIGHSC* for high self-control), and a condition in which half of the participants were randomly assigned to the tough and the placebo version, respectively (henceforth *MIXED* to denote the mixed nature of the market). In the *MIXED* condition, we will refer to traders facing the tough version of the Stroop task as *MIXLO* and to those facing the placebo version of the Stroop task as *MIXHI*, to avoid confusion with the pure treatments. Except for this treatment variation in part (ii), the two experimental conditions were identical in all other parts.

The Stroop task followed a simple protocol: participants were instructed to solve correctly 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 was to select the color of the font the word was printed in. A selection of six color buttons – always the same and in the same order – was given on the bottom right of the screen, and subjects were 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 was that the words always described one of the six colors; the incongruence between the color of the word and the word itself caused

Figure 1: Treatment Differences in the Stroop Task

a cognitive conflict, since reading the word was 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 had to be resolved, and resolution required self-control effort. Applying this effort depleted self-control resources and left participants with lower levels of willpower and/or 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/MIXLO* and *HIGHSC/MIXHI* was the frequency with which a conflicting word-color combination occurred.[9] All screens in *LOWSC/MIXLO* exhibited such a conflict, while in *HIGHSC/MIXHI* only every 70th screen did. Experimental participants did not receive any information on the frequency of such a conflict, and the instructions for the two versions of the task were identical. By having an occasional word-color incongruence in *HIGHSC/MIXHI* we were able to ensure that subjects take the task seriously. If anything, our setup reduced the potential treatment difference, because in *HIGHSC/MIXHI* some self-control depletion might still have taken place,

[9]The right-hand side of Figure 1 shows an example of congruence between font color and word, as we use it in the placebo Stroop task in *HIGHSC/MIXHI*.

making the potential result of a significant difference between the two conditions more difficult to obtain.

We decided to provide participants with a flat payment of €3.00 for the Stroop task in order to signal that we were interested in their performance. We did not use a piece-rate or any other competitive payment scheme because it might have created different wealth levels after the treatment variation, and wealth differences might be correlated with the treatment. Hence, treatment differences might have potentially been confounded by wealth effects.[10] Upon completion of the five minutes, we asked experimental participants how hard they perceived the task on a six-point Likert scale.

Self-control resource depletion can influence several relevant variables for the subsequent experimental asset market. We control for two mechanisms directly: cognitive ability and risk attitudes.[11] Eliciting control variables took place after the self-control manipulation but before the experimental asset market for two reasons: Firstly, if these measures had followed the asset market, there might have been spillover effects due to experiences during the asset market, and secondly, the effect of our self-control manipulation might have worn off since the asset market part of the experiment lasted a considerable amount of time during which self-control could start to regenerate (Muraven and Baumeister, 2000). In order to avoid that the self-control variation wore off before the asset market interaction started, it was a requirement that measuring the control variables did not take much time. Two tasks that fitted this requirement were 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-

[10] Achtziger et al. (2015) find 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; no one answered less than 110 items. Most of our subjects answered many more – see Appendix A.3 for details.

[11] For evidence of potential effects of self-control depletion on complex thinking see Schmeichel et al. (2003).

biases tasks (Toplak et al., 2011). Furthermore, Corgnet et al. (2014) and Noussair et al. (2014) find that the CRT is a good predictor of individual trader's profits in asset market experiments.[12] Subjects were paid €0.5 for every correct answer but did not learn their CRT results and thus 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 less frequently. On a single computer screen, our experimental participants had to choose ten times between a lottery that paid either €0.20 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 at most 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 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 (lasting 120 seconds each) in a continuous double-auction market design with ten traders and with open order books, following Kirchler et al. (2012).[13] This is a simplified version of the markets in Smith et al. (1988). Before the first trading period, five subjects in a given market received 1000 experimental points in cash and 60 assets, and the other five received 3000 points in cash and 20 assets as their initial endowment. Assignment to the two initial asset allocations was random.

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

[13] Appendix A.7 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 remain 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 payment 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 initially announced exchange rate of 500 points = €1.00.

In eight of the twelve sessions of the *MIXED* markets, we added several questions to the experimental questionnaires dealing with participants' emotions. We were interested 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 relevant at all to our question of interest. Four of those eight sessions asked subjects about their emotions not only after the ten trading periods, but also immediately after the first trading period.

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 how hard they have perceived decisions over the course of 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.

The sessions for the treatment *HIGHSC* and *LOWSC* were conducted in October 2013. 160 participants took part in 10 experimental sessions – 4 with one markets and 6 with two markets. Hence, we obtained 16 independent observations, 8 for each condition. We conducted a total of 12 sessions with 24 markets and 240 subjects of the *MIXED* treatment in April 2014, November 2015, and October 2017 (4 sessions each). In all, 400 subjects participated in 40 markets. The experiment was programmed using z-Tree (Fischbacher, 2007), and recruitment was done with the help of ORSEE (Greiner, 2015). Experimental sessions lasted for about 90 minutes, and participants earned €18.27 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.[14] Prior to the start of the experiment, subjects received written instructions for all parts of the experiment. These were read aloud to ensure common knowledge. Remaining questions were answered in private.

4 Experimental Results

4.1 Manipulation Check

The data suggest that our treatment manipulation was successful: First of all, during the Stroop task participants attempted fewer problems, achieved fewer correctly solved problems and made more mistakes in the *LOWSC/MIXLO* condition than in the *HIGHSC/MIXHI* condition (all Mann-Whitney tests $p < 0.01$, $N = 400$).[15] Participants perceived the Stroop task as significantly more demanding in the *LOWSC/MIXLO* condition than in the *HIGHSC/MIXHI* condition (Mann-Whitney test $p < 0.01$, $N = 400$). Finally, we do not find any differences in background characteristics such as field ($p = 0.695$, $N = 400$) and year of study ($p = 0.358$, $N = 400$), age ($p = 0.573$, $N = 400$) and gender ($p = 0.679$, $N = 400$) between our two treatments (Mann-Whitney

[14] Of our 400 subjects, 5 suffer 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.

[15] Detailed distributions on these variables can be found in section A.3 of the Appendix. All tests reported in this paper are two-sided unless stated otherwise.

tests and Pearson's χ^2 test for field of study), suggesting that random assignment to treatments was successful.

4.2 Definitions and Measures

In order to calculate mean prices one can use either an adjustment that takes trading volumes 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 the following.

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 Stöckl 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 overpricing, respectively.

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

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

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

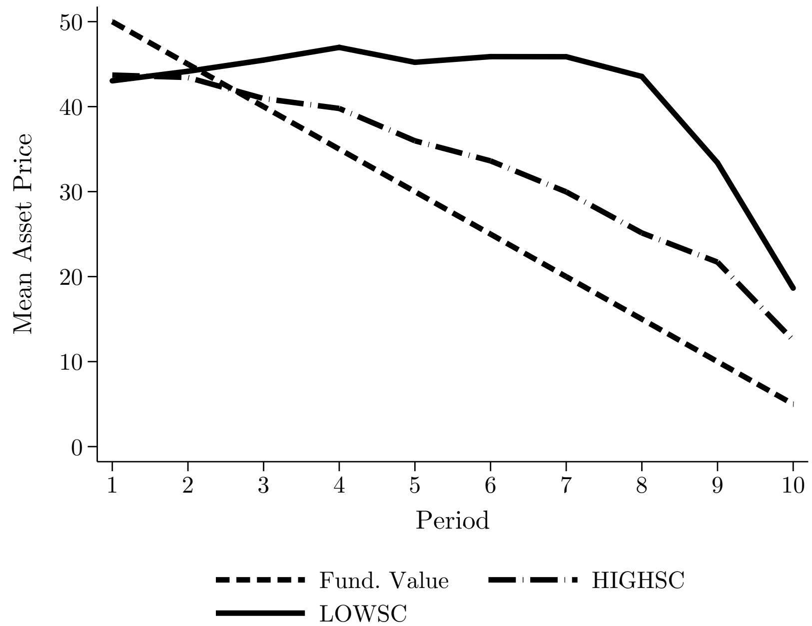

Figure 2: Mean (Volume-adjusted) Trading Prices in the Two Treatments

all deviations from the fundamental value – overpricing and underpricing – increase RAD, making RAD a measure of average mispricing. For RD the wedge between market price 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, in effect, a measure of average overpricing.

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

4.3 Aggregate Price Development

Figure 2 shows how average market prices in *LOWSC* and *HIGHSC* evolve over the ten trading periods. 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 the fundamental value. Eventually, average market prices drop sharply, but do not drop below the fundamental value again.

The most conservative comparisons between these two treatments are based on market averages over all traders and over all ten periods. This is the approach we apply for all non-parametric tests regarding aggregate market outcomes. These averages are statistically independent in the strict sense, and test statistics are based on eight observations for each of the two treatments. Thereby, we also eliminate all temporal correlation to make sure that our standard errors are not biased by autoregressive properties of the data. A Wilcoxon signed-ranks test confirms the impression from eyeballing, i.e. that market prices in both conditions are significantly different from the fundamental value (*HIGHSC*: $p = 0.0929$, *LOWSC*: $p = 0.0173$, $N = 8$). Figure 2 suggests more pronounced overpricing in the *LOWSC* condition than in *HIGHSC*, which is confirmed by a Mann-Whitney test (*HIGHSC*: $R\bar{D} = 0.1885$, *LOWSC*: $R\bar{D} = 0.4990$; $p = 0.0742$, $N = 16$)[16]. A comparison of RD tells us that while in *HIGHSC* overpricing is on average 19%, in *LOWSC* prices exceed the fundamental value by almost 50%. Thus, trade among individuals with low self-control leads to overpricing which is more than twice as high as in the baseline *HIGHSC*.

Furthermore markets in the *LOWSC* condition exhibit higher levels of mispricing (*HIGHSC*: $R\bar{A}D = 0.3253$, *LOWSC*: $R\bar{A}D = 0.5890$; Mann-Whitney test: $p = 0.0460$, $N = 16$). According to RAD, prices in the *HIGHSC* condition deviate by about 33% from the fundamental value, whereas they deviate by about 59% from the fundamental value in the *LOWSC* condition.

Figure 3 displays the price evolution of single markets in the two conditions. There is a high degree of path-dependence and endogeneity in price evolution in the markets and a lot of heterogeneity among markets in the same condition. Therefore, finding a significant difference between the two conditions for the most conservative test in terms of statistical independence is the more striking. The left panel represents the markets from the *HIGHSC* condition, while the right panel shows the *LOWSC* markets. Price paths in *HIGHSC* markets often follow a rather flat or declining development, while in *LOWSC* a number of markets display a hump-shaped price evolution that

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

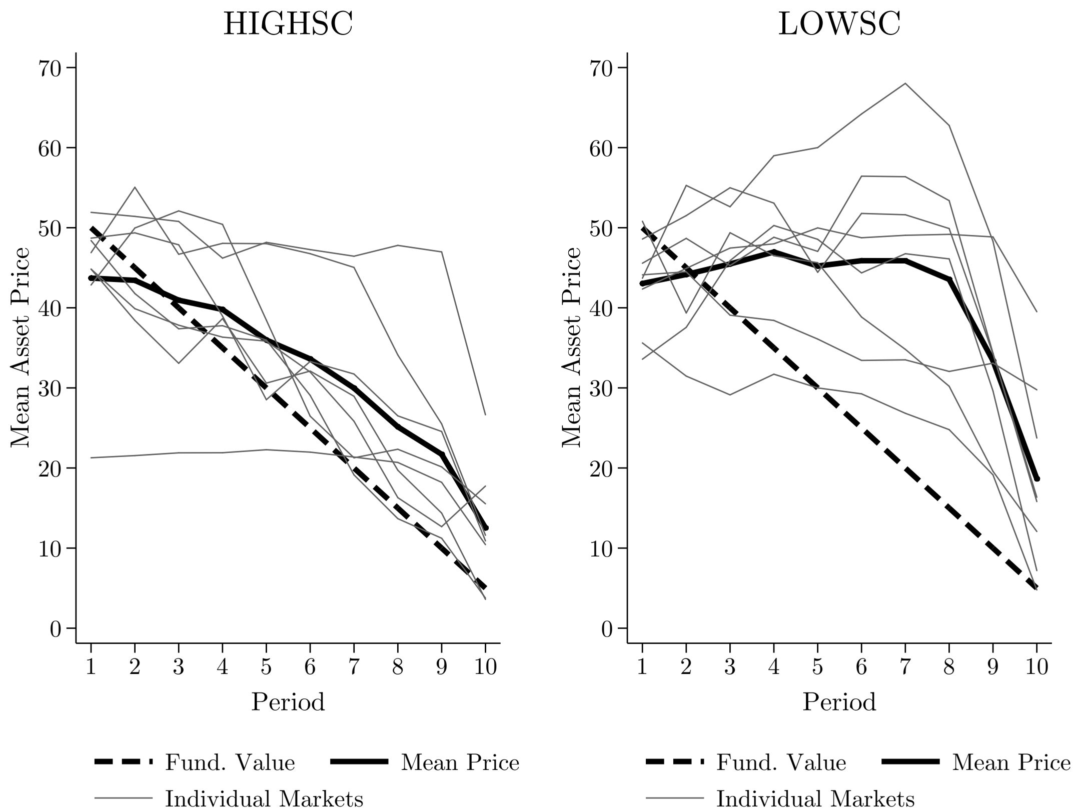

Figure 3: Evolution of Individual Market Prices in *HIGHSC* and *LOWSC*

initially increases and peaks in later trading periods. The emergence of overpricing oftentimes can be attributed to constant prices despite decreasing fundamental values (Huber and Kirchler, 2012; Kirchler et al., 2012) – a description that fits price paths in our *HIGHSC* markets better than those in *LOWSC* markets.[17]

Figure 4 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 changed if only part of the trader population is self-control depleted. Both *LOWSC* and *MIXED* on average display more overpricing than *HIGHSC*. For *MIXED* we observe an average RAD of 0.529 and an average RD of 0.398. A Mann-Whitney test confirms that the mispricing measure RAD in *MIXED* is significantly

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

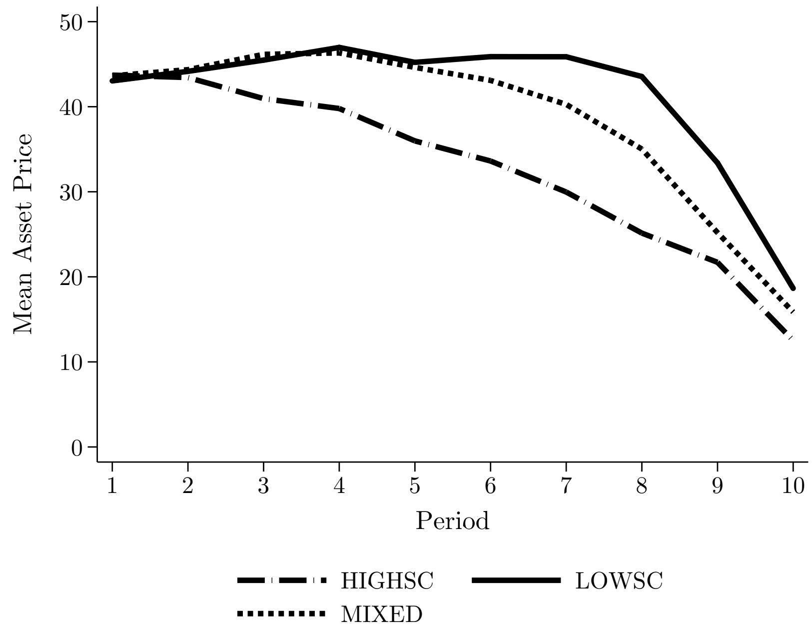

Figure 4: Trading Price Evolution Including *MIXED*

different from *HIGHSC* ($p = 0.056$, $N = 32$) but cannot be statistically distinguished from *LOWSC* ($p = 0.5716$, $N = 32$). This result also holds for our overpricing measure: RD in *MIXED* differs significantly from *HIGHSC* ($p = 0.0982$, $N = 32$), but not from *LOWSC* ($p = 0.4334$, $N = 32$).[18] Figure 5 illustrates the evolution of mean trading prices for the 16 individual markets in the *MIXED* condition. Qualitatively, we get similar results as in *LOWSC*. That is, 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 depleted self-control abilities is sufficient to reproduce the excess overpricing we observed when all traders' self-control levels were depleted.

[18]The results of these comparisons also hold when looking at quantity- or trade-adjusted mean prices.

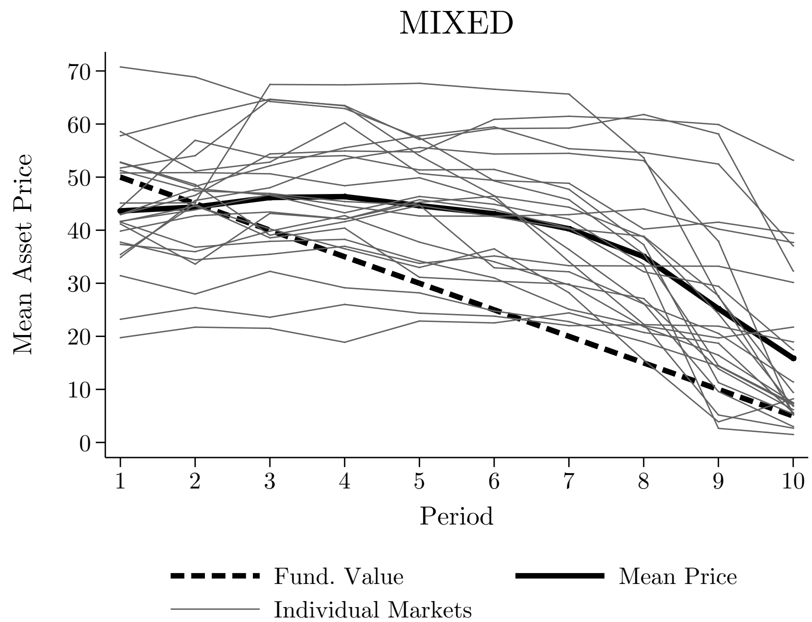

Figure 5: Price Evolution in Individual Markets in *MIXED*

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 had an effect on market outcomes. Detailed descriptive results on the variables considered in this section can be found in sections A.4ff. 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 scores between the two conditions is not significant according to a Mann-Whitney test ($p = 0.7223$, $N = 160$). We conclude that the Stroop task did not have an impact on our incentivized version of the CRT.[19] Risk attitudes might be affected by self-control depletion. The average certainty equivalent we elicited is close to the lottery's expected value: 2.2 in *HIGHSC* and 2.15 in *LOWSC*. Like the literature exploring the

[19] If we include the observations from the *MIXED* conditions, the CRT scores of the two groups become 1.08 and 1.18 respectively with $p = 0.3911$, $N = 400$ from a Mann-Whitney test.

effect of reduced self-control on risk attitude that has come to inconclusive results (e.g. Bruyneel et al., 2009; Unger and Stahlberg, 2011; Gerhardt et al., 2017), we also find no significant effect (Mann-Whitney test, $p = 0.4083$, $N = 160$) of our treatment variation on risk attitudes as measured by the multiple price list certainty equivalent elicitation.[20]

Although our control variables seem unaffected by our treatment, they could still possess explanatory power for the difference in overpricing that we observe. We therefore run regressions, including controls as indepedent variables. To avoid endogeneity problems across trading periods and between subjects, respectively, we aggregate overpricing measures over all ten 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 as before. We report results on $IndRD_{purchases}$ as the dependent variable in the regressions in Table 1. In Appendix A.2, we provide robustness checks for our chosen approach for sales and both aggregated sales and purchases.

In all four models we are interested in the effect of the explanatory variables on $IndRD_{purchases}$, our measure of an individual's overpricing tendency. Throughout all specifications, we observe a significant treatment effect: Being in *LOWSC* increases an individual's propensity to buy at excessive prices. In specification (2), our measure of risk attitude is not significant, but if we also include interactions with our treatments in specifications (3) and (4), relative risk seeking is correlated with lower individual overpricing when self-control capabilities are reduced. Performance on the CRT has the expected effect of reducing the tendency of buying at prices above fundamental value in all specifications where it is included, although not always statistically significant, and

[20]Including observations from the *MIXED* conditions also does not provide significant differences between the two groups: $p = 0.9134$, $N = 400$.

	(1)	(2)	(3)	(4)
		$IndRD_{purchases}$		
LOWSC	0.369**	0.390**	0.816***	0.843***
	(0.136)	(0.134)	(0.131)	(0.125)
CRT		-0.0708*	-0.0952	-0.0912
		(0.0392)	(0.0558)	(0.0547)
CE		-0.0188	0.0684	0.0719
		(0.0459)	(0.0441)	(0.0455)
CRT × *LOWSC*			0.0612	0.0628
			(0.0821)	(0.0831)
CE × *LOWSC*			-0.224***	-0.237***
			(0.0712)	(0.0709)
Female				0.0666
				(0.0690)
Constant	0.084	0.194	0.0255	-0.0353
	(0.082)	(0.120)	(0.0597)	(0.0682)
Observations	160	110	110	110
R^2	0.227	0.307	0.364	0.370

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. Subjects who indicated they knew one or more of the CRT questions before were excluded from columns (2) through (4). 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

its effect does not significantly differ between participants in *LOWSC* and *HIGHSC* markets.[21] Hence, introducing measures for risk aversion and cognitive skills and their interactions with our treatments do not reduce the size or significance of the treatment coefficient. We conclude that neither changes in cognitive skills nor in risk preferences can explain our main result of excess overpricing after self-control depletion.

[21]Note that we exclude subjects who were familiar with the CRT from all regressions including this variable, since such knowledge might have inflated correct CRT responses and thus obfuscate any effects of CRT scores. The regression results are qualitatively very similar when including these subjects.

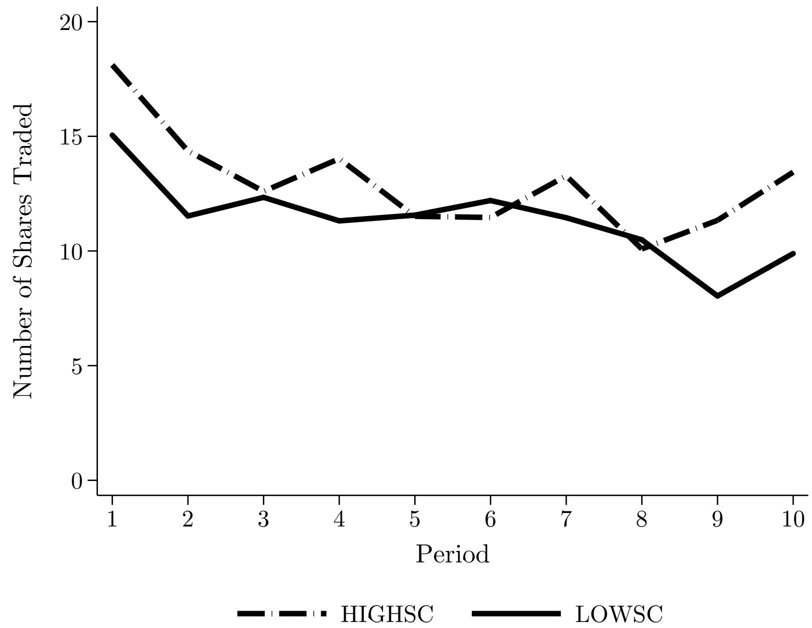

Figure 6: Evolution of Average Shares Traded per Trader by Condition

4.4.2 Trading Activity

An additional channel through which our results could be explained is changes in trading activity, i.e. the number of traded shares per trading 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, could be responsible for our results. Thus we compare the number of shares traded in the two conditions. Figure 6 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 between the two conditions ($p = 0.3446$, $N = 16$).[22]

We therefore turn to our *MIXED* condition. We investigate if we can find differences in trading behavior when both treated and untreated traders interact in the same market. However, when

[22] An additional regression analysis in Table 6 in Appendix A.2 reinforces this conclusion.

	Group Mean		
	MIXHI	*MIXLO*	p-value
$\overline{p_{bid}}$	35.927	28.539	0.044**
$\overline{p_{ask}}$	59.303	53.097	0.753
$\overline{q_{bid}}$	14.511	17.076	0.119
$\overline{q_{ask}}$	12.940	13.813	0.627
$\overline{time_{bid}}$	60.732	47.318	0.044**
$\overline{time_{ask}}$	51.410	51.194	0.954
$\overline{firsttime_{bid}}$	52.978	41.458	0.108
$\overline{firsttime_{ask}}$	34.176	36.358	0.690

Variables starting with a p denote prices, q quantities and time variables refer to the time passed in the current period, thus lower values indicate behavior earlier on. *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

Table 2: First Period Differences in Trading Behavior

analyzing trading behavior, distinguishing cause and effect is particularly difficult, as most of the trading behavior may be endogenous due to interactions across traders. A particular deviation in behavior by some traders in the early phases of a market might shift behavior of other (non-depleted) traders. We therefore start by focusing on the very first trading period, where dependencies are less relevant than in later periods. Table 2 compares several variables concerning trading activity between *MIXLO* and *MIXHI* traders.

According to Wilcoxon signed-rank tests *MIXLO* traders make significantly lower bids initially ($p = 0.044$, $N = 22$) and post these bids earlier than their non-depleted peers ($p = 0.044$, $N = 22$). They are also quicker in posting their first bid at the beginning of the period but this test barely misses conventional significance levels ($p = 0.108$, $N = 22$). After period one, these differences vanish, suggesting that non-depleted traders start imitating the behavior of self-control depleted traders.[23]

The non-difference in trading activity between *HIGHSC* and *LOWSC*, as well the earlier bidding in the mixed condition raises the question if it violates the observation of Baumeister et al. (1998) that subjects with depleted self-control capabilities become more passive. The authors of that

[23]Results for period two are reported in Table 12 of the Appendix indicating that these initial trading differences disappear.

paper define ‘passive’ as following usual action patterns without deliberations, while they define ‘active’ as the result of cognitive effort to determine the best action to be chosen. As an example, they describe a married couple deciding whether to go to sleep. While the decision to go to bed could be considered ‘active’ in terms of movement, it may also be ‘passive’ if the couple does so as part of a routine. We think that ‘passiveness’ in our experiment should be understood in the same way. Posting lower bids earlier seems more in line with ‘passivity’, i.e. an automatism, without much active deliberation. Instead, thinking about the value of the asset and strategies to arbitrage against other players requires one to be cognitively active.

4.5 Profits

On average, *MIXLO* traders earned € 8.23, and *MIXHI* traders earned € 7.77 in the experimental asset market – a difference that is not significant (Wilcoxon signed-rank test, $p = 0.2531$, $N = 24$). We consider this as evidence that inhibited self-control abilities affect overpricing, but that depleted traders are not necessarily driven out of the market. This is very well in line with our findings from the previous section on trading activity. Because trading behavior only differs significantly during the first period and converges afterwards, traders eventually become indistinguishable in their behavior. With similar profits, all that low self-control traders have achieved is to shift markets onto different price trajectories. The lack of a difference in profits may thus be a reason for why such a behavioral bias may persist.

Previous research has furthermore 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. Thus, we can interpret the CRT score as a measure of cognitive control. In order to check whether the effect of CRT performance on profits is similar here, we ran additional regressions which we report in Table 3. Note that we excluded participants who had indicated that they knew at least one of the CRT questions at the end of the experiment. The knowledge of CRT questions before the experiment might have inflated correct CRT responses and thus obfuscate any interaction effects between treatment and CRT scores.[24]

In specification (1) we reproduce the finding that there is no statistically significant difference between the profits of traders in *MIXLO* and *MIXHI*. Specification (2) confirms findings from earlier studies that higher CRT scores are positively related to higher overall profits for both *MIXLO* and *MIXHI*. However, when we separate this effect by treatment by including an interaction of 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 ($p < 0.01$) and in fact cannot be distinguished from zero overall (post-estimation Wald test, $p = 0.56$).

Thus, *MIXLO* subjects' trading seems to be relying less on their underlying ability for cognitive control. Together with the results indicating higher emotional valence and reactivity that we will present below, this suggests an interpretation of trading behavior of *MIXLO* participants as relatively more relying on impulsive system 1 processes than on reflective system 2 processes (Kahneman, 2011).[25]

4.6 Increased Emotional Reactivity

In the experimental sessions that we conducted in November 2015 and October 2017, we asked participants a number of questions relating to their emotional experience during trading in the asset market. 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. We asked participants at the end of the experiment, requiring them to recollect their emotions.[26] In the

[24] 72 subjects in *MIXED* markets reported to know at least one of the CRT questions. Including these subjects makes the coefficient of the interaction term CRT $\times$ MIXLO insignificant in the specifications parallel to (3) and (4) as these subjects water down the effect.

[25] Hefti et al. (2016) argue that good performance in an asset market requires two dimensions of cognitive capabilities, mentalizing and cognitive abilities. Self-control depletion could in principle affect both dimensions and lead subjects to become more impulsive. We deem this an interesting question for future research.

[26] We also provided participants with a questionnaire regarding their trading behavior which we do not report here. The average responses to all the emotion-related questions and the test statistics can be found in Table 8 of the Appendix. Average values for changes in emotions over time can be found in Table 9.

	(1)	(2)	(3)	(4)
		Profit		
MIXLO	0.468	0.924	3.803**	3.855**
	(0.377)	(0.591)	(1.776)	(1.797)
CRT		0.960**	1.747***	1.6776**
		(0.356)	(0.469)	(0.508)
CE		0.325	0.607	0.443
		(0.426)	(0.580)	(0.575)
CRT × MIXLO			-1.484***	-1.419**
			(0.507)	(0.530)
CE × MIXLO			-0.839	-0.853
			(0.843)	(0.834)
Female				-1.045
				(0.634)
Constant	7.035***	5.723***	4.617***	5.689***
	(0.320)	(0.906)	(1.097)	(1.288)
Observations	240	137	137	137
R^2	0.004	0.081	0.121	0.138

Participants who indicated to know at least one of the CRT questions excluded in columns (2)-(4); robust standard errors clustered on the market level in parentheses; *** p<0.01, ** p<0.05, * p<0.1

Table 3: Determinants of Profits in *MIXED*

sessions conducted in October 2017, we additionally asked participants for their emotions directly after the first trading period, to assess whether their recollection is accurate.

Table 4 reports the results for those emotions that have previously been connected to overpricing in experimental asset markets (Hargreaves Heap and Zizzo, 2011; Andrade et al., 2016; Lahav and Meer, 2012; Breaban and Noussair, 2018). 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, the intensity of 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 ($p = 0.168$) and significantly more joy ($p = 0.097$). Remember that Lahav and Meer (2012) found that inducing positive mood before trading leads to higher deviations from fundamental values and thus larger levels of overpricing and that correlational studies also suggest such a relationship (Breaban and

	MIXHI	MIXLO	p-value	N
Beginning of the First Period				
Excitement	4.088	4.325	0.300	16
Fear	2.113	2.200	0.717	16
Surprise	3.475	3.813	0.168	16
Joy	3.475	3.888	0.097*	16
End of the Last Period				
Excitement	3.538	4.175	0.030**	16
Fear	2.163	2.513	0.014**	16
Surprise	2.788	3.350	0.066*	16
Joy	3.188	3.813	0.055*	16
Asked after the First Period				
Excitement	3.925	4.200	0.483	8
Fear	2.325	2.475	0.833	8
Surprise	2.900	3.350	0.056*	8
Joy	2.800	3.275	0.139	8
Self-Evaluation of Emotional Reactivity				
Emotion driven	2.600	2.925	0.066*	16
Suppressed emotions	4.913	4.713	0.468	16

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 4: Ex-post Reported Emotions of Traders in *MIXED*

Noussair, 2018; Hargreaves Heap and Zizzo, 2011). Furthermore, at the end of the final trading period, *MIXLO* traders report significantly higher levels of excitement, fear, joy and surprise than *MIXHI* participants (all $p < 0.1$, excitement and fear $p < 0.05$). When asked for their emotions directly after the first period, subjects also report stronger emotions when self-control depleted, although only surprise is significantly different. The general picture, however, suggests that the emotional experience of the asset market was very different for these traders.

We also asked participants in the post-experimental questionnaire explicitly about how strongly they felt their behavior was driven by emotions and how much they had tried to suppress the influence of emotions on their trading behavior (see final panel of 4). *MIXLO* participants report to have acted much more emotion driven ($p = 0.066$). They also report lower levels of emotion supression, but the differences fail to reach significance at conventional levels. The results indicate that the behavior of the traders with depleted self-control abilities might have been driven by emotional factors to a larger degree than they were aware of themselves.

Due to existing findings, initial differences before the opening of the asset market (and after the Stroop task) are one channel via which depleted self-control could have affected overpricing. Apart from the pre-market emotional state, differential emotional reactions during the market could be driving our results. Emotion regulation has been shown to draw on self-control resources (Baumeister et al., 1998; Hagger et al., 2010). We have evidence that participants displayed more intense emotional states, in particular at the end of the asset market. We interpret our treatment effect as the result of an increased sensitivity towards emotions triggered by self-control depletion. 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 in product choice. Similarly, in our setting traders with low self-control levels could rely more heavily on affective features of the asset, 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 more myopic decision making, a higher level of overconfidence/overoptimism (Michailova and Schmidt, 2016), and more speculative trading.

5 Welfare Implications

While we establish a strong effect of reduced self-control on prices, there remains an important question: Is welfare affected? After all, real life asset markets exist because trade can be welfare-improving.[27] We therefore discuss how our setting can be informative for markets outside the laboratory.

First, we think that even a setup using a zero-sum game can be informative. Note that under the restrictive assumption of risk-neutrality, we should not observe any trades. With heterogeneity

[27] We are very grateful to Wei Jiang and two anonymous referees for raising this question.

in risk preferences (which we observe), however, trade can be welfare improving, if the risk (of the stochastic asset) is transferred from risk-averse to risk-loving traders. This is exactly the kind of welfare improvement that real asset markets generate. Technically, trading an asset is only a zero-sum exchange of money for assets, while the valuations (e.g. due to different risk profiles) of investors may differ. Therefore, the fact that our depleted traders trade at higher prices without measurable changes in risk preferences must be, on average, welfare-decreasing if the choices at higher levels of self-control were optimal. This, we argue, constitutes a reasonable assumption, given that our previous findings have shown that depleted subjects seem to act more emotionally and therefore less deliberatively.

Second, one could understand the particular experimental asset market as a partial equilibrium depiction of a real asset market. Assuming that some investors with market power have information about the value of the asset while others without market power have not, prices may then be used as signals by uninformed investors (Fama, 1970; Grossman, 1976; Wolinsky, 1983; Radner, 1979). Higher prices generated due to a lack of self-control of informed traders could entice other traders to wrongly invest in inferior assets, thereby harming welfare as more lucrative options are passed on. This might even happen, as our *MIXED* treatment shows, when only a moderate share of traders is low in self-control.

To show that uninformed traders actually make wrong investment choices, we report results from another experiment, conducted in January 2018. We invited 96 subjects in 4 sessions to the laboratory and made them choose repeatedly between an asset with known value, and an unknown asset where they only could observe the trading price. In 20 decisions, appearing in random order for each subject, the unknown asset's trading price was simply the average trading price from each of the 10 periods of our *LOWSC* and our *HIGHSC* treatments. The asset with known value was always superior to the value underlying the unknown asset. In each decision, subjects received 100 points to distribute among the known asset and the unknown asset. Subjects were made aware that the unknown asset's price was determined by other human traders who were informed about the asset's value.[28]

We observe that subjects invest on average 58.60 points in the inferior asset when prices were generated by the traders in the *LOWSC* treatment, but only 43.91 points when prices were generated by the traders in the *HIGHSC* treatment. This difference is highly significant according to a Mann-Whitney test ($p < 0.01$, $N = 96$). Optimal choices would have required an investment of 0 points in the unknown asset, such that low self-control traders raise the existing inefficiency by about 33%, severely harming welfare, compared to the high self-control traders. Taking these two arguments together suggests that excessively high prices may harm welfare substantially.

6 Conclusion

In this paper, we provide causal empirical evidence for the notion that a lack of self-control can fuel overpricing on asset markets. We consider experimental continuous double auction markets for which Smith et al. (1988) first reported a tendency for overpricing. We exogenously reduce market participants' ability to exert self-control using a tough version of the Stroop task, which has previously been shown to deplete people's ability to exert self-control in subsequent tasks (Baumeister et al., 1998). Comparing three market settings in which either everyone's, or half of the traders', or no one's self-control was reduced, we observe significantly more mispricing and overpricing as the result of a reduction in self-control abilities than without this reduction.

Self-control depletion affects trading behavior and the perception of the trades and market outcomes. We provide evidence that in markets populated by self-control depleted and non-depleted traders initial bidding behavior is different across the two groups. However, the evidence is not entirely conclusive. Trading on experimental asset markets is path-dependent, and it is difficult to pin down the exact reasons for overpricing to emerge without making arbitrary assumptions. We do not observe a performance difference between traders with depleted self-control and traders with

[28]Instructions are provided in Appendix A.7.2.

full self-control abilities, suggesting that low self-control traders might not be driven out of the market. While we would expect a market to self-regulate in the aggregate, this fact shows why this particular behavioral bias may persist.

In addition, we have evidence for an emotional channel that explains our main result. Self-control depleted traders show stronger emotions, in general, but in particular stronger emotions that have been linked to overpricing in previous studies that induce emotions or that measure emotions while trading. Finally, we find that our measure for cognitive skills loses predictive power for the profits of low self-control traders. This might indicate that even though cognitive skills seem unaffected by self-control depletion (as are risk attitudes), different cognitive processes play a role in traders with low self-control levels. These results are in line with a dual systems perspective of self-control: self-control depleted participants seem to have acted more on the basis of emotions and less on the basis of cognition, thus driving up prices. We discuss that higher prices may be an issue from a welfare perspective, as they distort traders' decisions and may serve as signals for uninformed buyers.

Our findings have relevant implications: First, with differences in self-control levels, we add a potentially important explanation to the existing explanations for overpricing on asset markets. We have shown that already a moderate number of participants with low self-control levels are sufficient to more than double the extent of overpricing in terms of relative deviation from fundamental value. Second, our results can be regarded as indicative of the role of self-control in markets outside the laboratory – there, both temporary reductions in self-control as well as the personality trait self-control might play an important role in determining trading behavior and perception. Self-control might also be an important attribute on which individuals self-select into trading. However, low self-control traders might not be as easily exploitable by high self-control traders as one would think. In our case, they would not have been driven out of the market quickly.

Several practical implications of our results for investing and trading activities from a welfare perspective 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 consequences for prices and welfare. This might be particularly relevant in fast-paced markets.

Our experiment opens up interesting paths for future research: It would be interesting to see to what extent our results are robust to changes in alternative market mechanisms such as call markets and to changes in the fundamental value process such as a constant fundamental value process, which has been shown to reduce overpricing (Kirchler et al., 2012). Finally, the role of self-control for traders in markets outside the laboratory remains largely unexplored. One can imagine field experiments or using quasi-experimental variations of self-control abilities to study decisions of traders on real markets.

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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 significance levels 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	-0.050	-2.915	-3.038
	(1.646)	(2.032)	(4.235)	(4.562)
CRT		-0.029	-1.310*	-1.328*
		(0.842)	(0.700)	(0.716)
CE		0.685	0.558	0.542
		(0.802)	(0.820)	(0.868)
CRT × *LOWSC*			2.881*	2.874*
			(1.525)	(1.537)
CE × *LOWSC*			0.278	0.335
			(1.700)	(1.922)
Female				-0.295
				(1.942)
Constant	13.02***	11.06***	12.42***	12.69***
	(0.750)	(2.173)	(2.280)	(3.313)
Observations	160	110	110	110
R^2	0.012	0.006	0.035	0.036

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. Subjects who indicated they knew one or more of the CRT questions before were excluded. 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)
		Average quantity traded		
MIXLO	-1.719	-0.617	-1.041	-0.997
	(1.105)	(1.474)	(3.979)	(4.004)
CRT		-1.167*	0.101	0.044
		(0.602)	(1.106)	(1.128)
CE		1.547*	1.127	0.990
		(0.749)	(0.985)	(1.061)
CRT × MIXLO			-2.359	-2.304
			(1.382)	(1.376)
CE × MIXLO			1.013	1.001
			(1.656)	(1.655)
Female				-0.869
				(1.277)
Constant	11.91***	8.86***	8.82***	9.71***
	(1.142)	(1.470)	(1.999)	(2.648)
Observations	240	137	137	137
R^2	0.013	0.041	0.062	0.065

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. Subjects who indicated they knew one or more of the CRT questions before were excluded. 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	4.088	4.325	0.300
Fear1	2.113	2.200	0.717
Surprise1	3.475	3.813	0.168
Anger1	1.838	2.063	0.717
Relief1	2.688	3.050	0.108
Sadness1	1.700	1.850	0.623
Joy1	3.475	3.888	0.097*
Excitement2	3.538	4.175	0.030**
Fear2	2.163	2.513	0.107
Surprise2	2.788	3.350	0.067*
Anger2	2.025	2.113	0.565
Relief2	3.050	3.775	0.024**
Sadness2	2.150	2.013	0.660
Joy2	3.188	3.813	0.055*
Emotion intensity	2.733	3.067	0.014**
Emotion valence	1.288	1.648	0.148
Emotion intensity1	2.768	3.027	0.079*
Emotion valence1	1.548	1.731	0.326
Emotion intensity2	2.700	3.107	0.004***
Emotion valence2	1.319	1.556	0.352

Note: p-values from Wilcoxon-Signed Rank tests collapsing data on the market level by *MIXLO* and *MIXHI* respectively; emotion intensity is the average score over all emotion questions, emotion valence is the average score over all positive emotions minus the score over all negative emotions; variables ending in 1 or 2 relate to questions at the beginning (1) or the end (2) of the asset 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	-0.550	-0.150	0.120
Diff fear	0.050	0.400	0.107
Diff surprise	-0.688	-0.463	0.452
Diff anger	0.188	0.050	0.756
Diff relief	0.362	0.725	0.205
Diff sadness	0.450	0.163	0.436
Diff joy	-0.288	-0.075	0.660

Note: p-values from Wilcoxon-Signed Rank tests collapsing data on the market level by *MIXLO* and *MIXHI* 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**	0.350**	0.605**	0.648**
	(0.147)	(0.143)	(0.243)	(0.221)
CRT		-0.0488	-0.0774	-0.0712
		(0.0395)	(0.0613)	(0.0608)
CE		0.00173	0.0584	0.0639
		(0.0551)	(0.0617)	(0.0634)
CRT × *LOWSC*			0.0684	0.0709
			(0.0800)	(0.0782)
CE × *LOWSC*			-0.146	-0.167
			(0.109)	(0.106)
Female				0.103
				(0.0655)
Constant	0.172	0.210	0.111	0.0164
	(0.106)	(0.147)	(0.104)	(0.110)
Observations	160	110	110	110
R^2	0.188	0.241	0.269	0.283

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. Subjects who indicated they knew one or more of the CRT questions before were excluded. 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**	0.375**	0.723***	0.760***
	(0.137)	(0.134)	(0.160)	(0.147)
CRT		-0.0593	-0.0775	-0.0722
		(0.0349)	(0.0574)	(0.0568)
CE		-0.0155	0.0553	0.0600
		(0.0457)	(0.0461)	(0.0475)
CRT $\times$ *LOWSC*			0.0461	0.0483
			(0.0722)	(0.0728)
CE $\times$ *LOWSC*			-0.182**	-0.200**
			(0.0784)	(0.0774)
Female				0.0884
				(0.0584)
Constant	0.119	0.203	0.0648	-0.0159
	(0.0979)	(0.125)	(0.0713)	(0.0774)
Observations	160	110	110	110
R^2	0.265	0.326	0.370	0.382

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. Subjects who indicated they knew one or more of the CRT questions before were excluded. Heteroskedasticity robust standard errors clustered at market level in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Table 11: Determinants of Individual Miscpricing

	Group Mean		
	MIXHI	*MIXLO*	p-value
$\overline{p_{bid}}$	30.713	30.830	0.677
$\overline{p_{ask}}$	52.136	56.543	0.170
$\overline{q_{bid}}$	14.275	14.454	0.728
$\overline{q_{ask}}$	11.273	12.486	0.219
$\overline{time_{bid}}$	57.386	46.291	0.259
$\overline{time_{ask}}$	47.892	50.038	0.502
$\overline{firsttime_{bid}}$	49.761	38.538	0.322
$\overline{firsttime_{ask}}$	27.432	30.849	0.376

Variables starting with a p denote prices, q quantities and time variables refer to the time passed in the current period, thus lower values indicate behavior earlier on. *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

Table 12: Second-Period Differences in Trading Behavior

A.3 Distribution of Answers in the Stroop Task

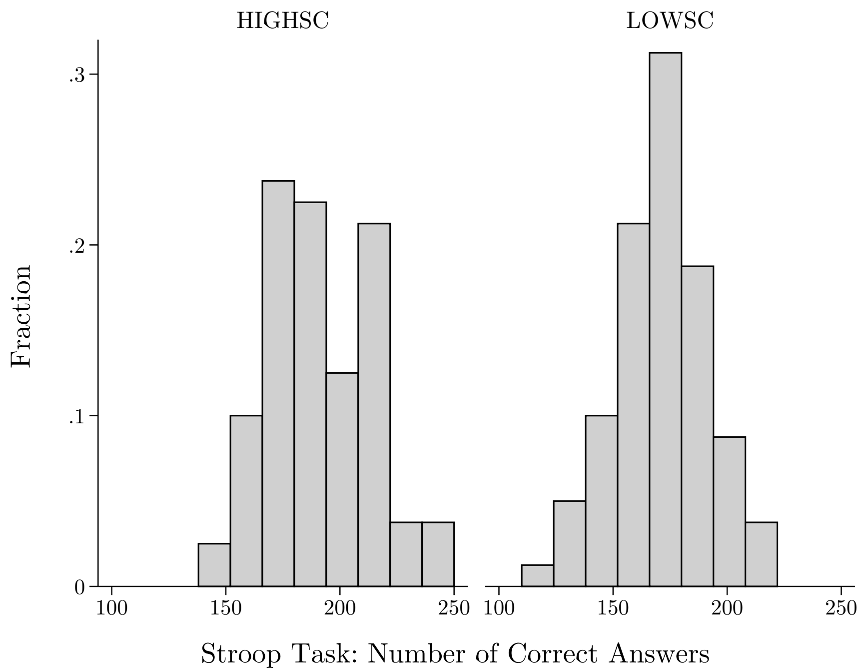


Figure 7: Correct Stroop responses in *HIGHSC* vs. *LOWSC*

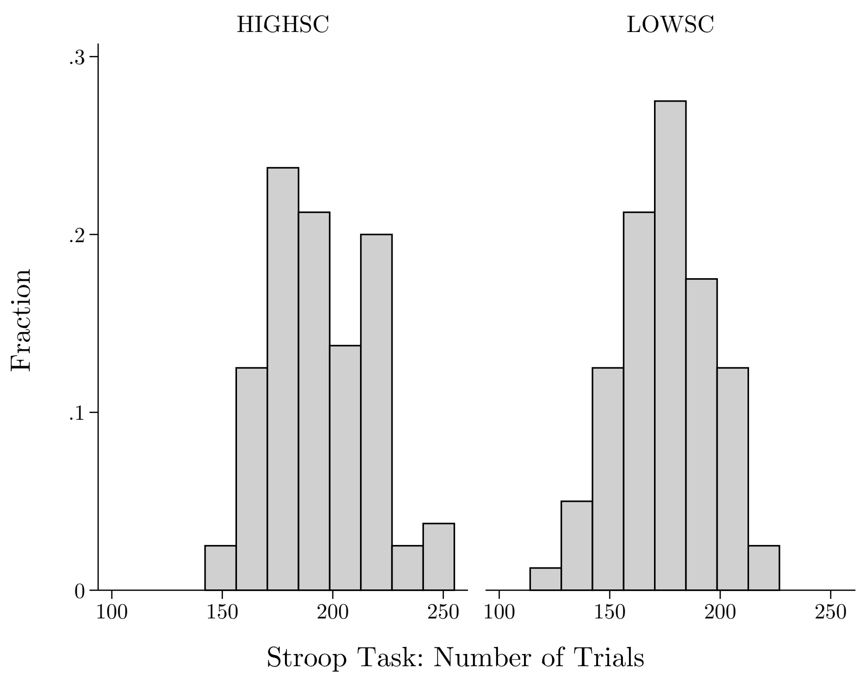


Figure 8: Stroop Trials in *HIGHSC* vs. *LOWSC*

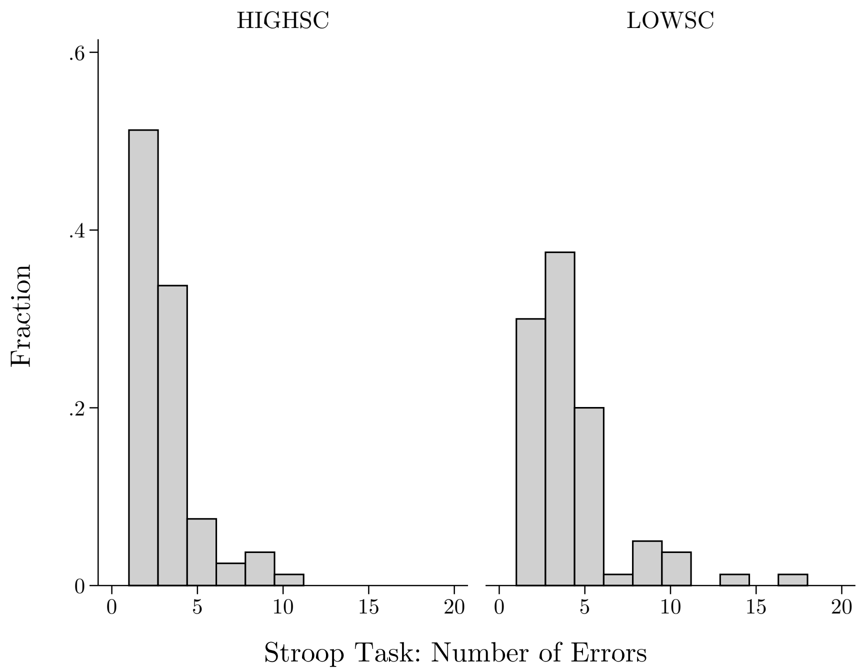


Figure 9: Errors in the Stroop Task in *HIGHSC* vs. *LOWSC*

Distribution of Answers in the Stroop Task

HIGHSC	Mean	Standard deviation
Correct Answers	191.65	22.6146
Trials	194.55	23.55973
Errors	2.9	1.879941
LOWSC	**Mean**	**Standard deviation**
Correct Answers	170.3125	20.68363
Trials	174.45	20.96948
Errors	4.14	2.971356

Table 13: Distribution of Answers in the Stroop Task

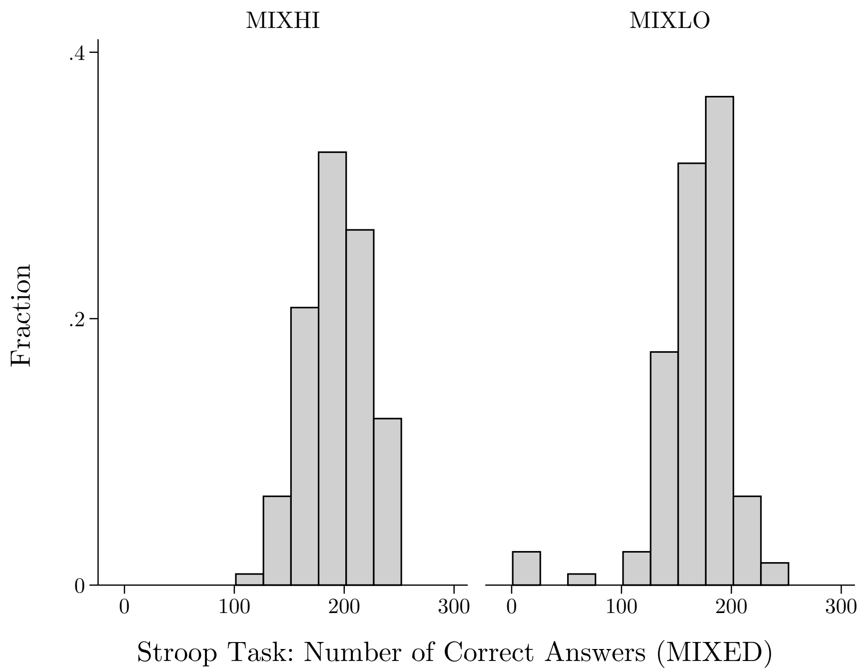


Figure 10: Correct Stroop Responses in Treatment *MIXED* by Condition

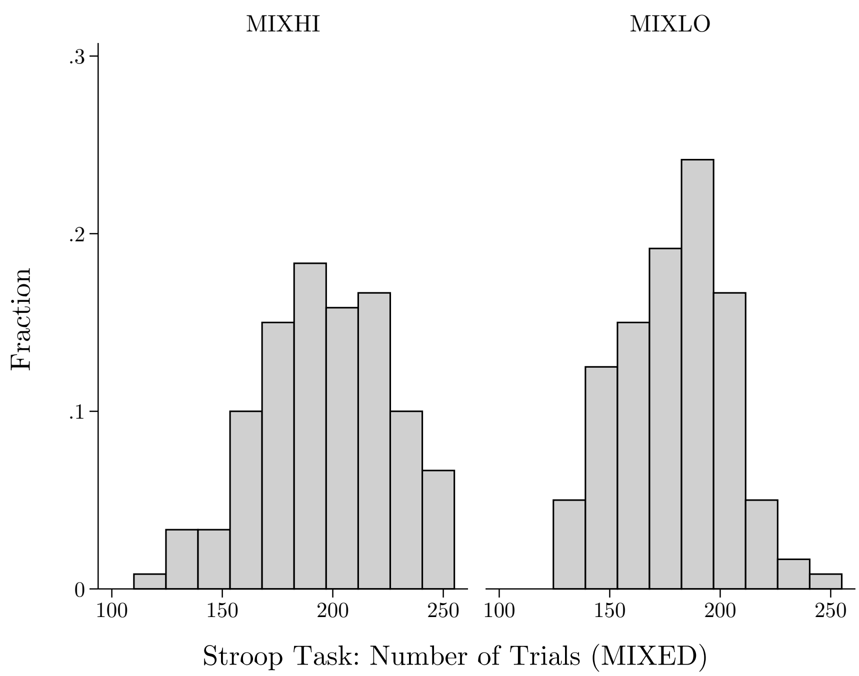


Figure 11: Stroop Trials in Treatment *MIXED* by Condition

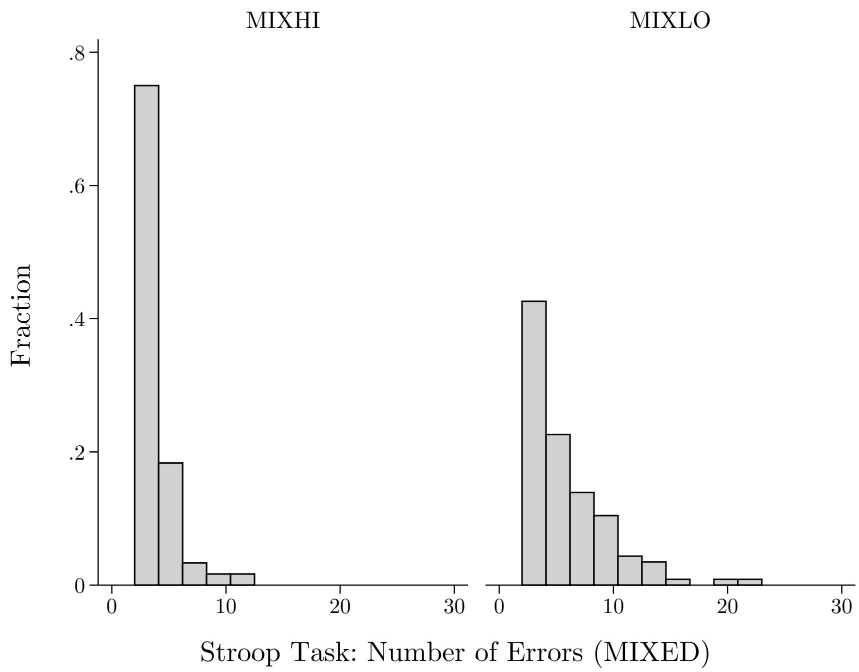


Figure 12: Errors in the Stroop Task in Treatment *MIXED* by condition[29]

[29]Four outliers were dropped from this display in the *MIXLO* group, as they apparently did not fully understand the task. They had between 124 errors and 206 errors.

Distribution of Answers in the Stroop Task (MIXED)		
MIXHI	Mean	Standard deviation
Correct Answers	191.633	29.179
Trials	195.3667	29.798
Errors	3.733	1.799
MIXLO	Mean	Standard deviation
Correct Answers	166.55	37.564
Trials	178.825	24.888
Errors	12.275	32.694

Table 14: Distribution of Answers in the Stroop Task (MIXED)

A.4 Distribution of Subjective Measures

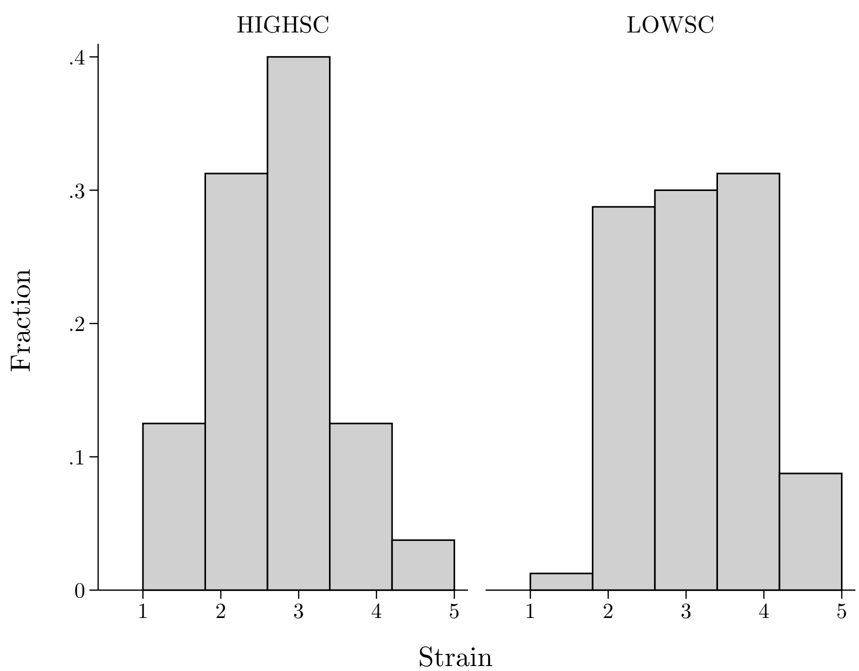


Figure 13: Strain in *HIGHSC* vs. *LOWSC*

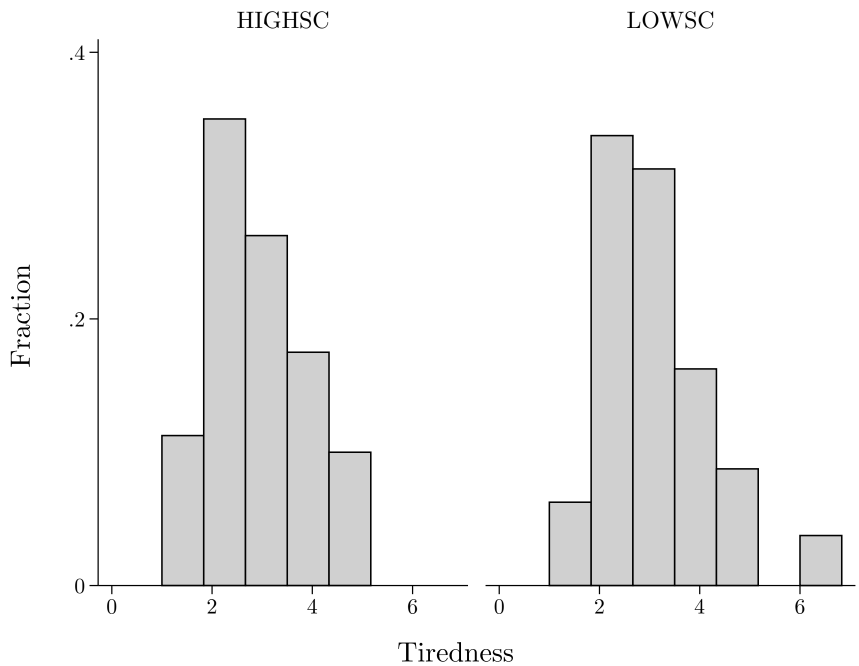


Figure 14: Tiredness in *HIGHSC* vs. *LOWSC*

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

Table 15: Distribution of Subjective Measures

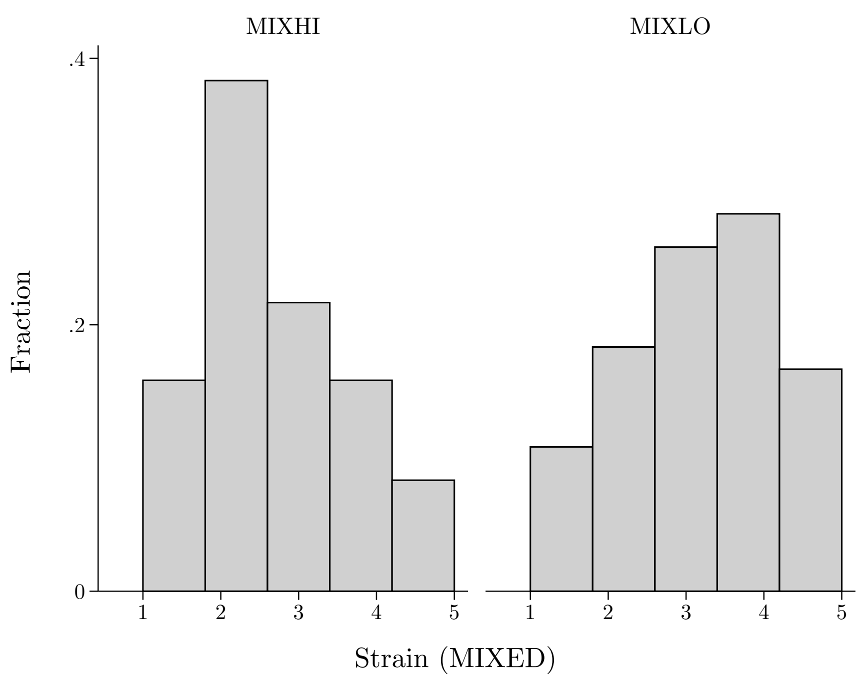


Figure 15: Strain in Treatment *MIXED* by Condition

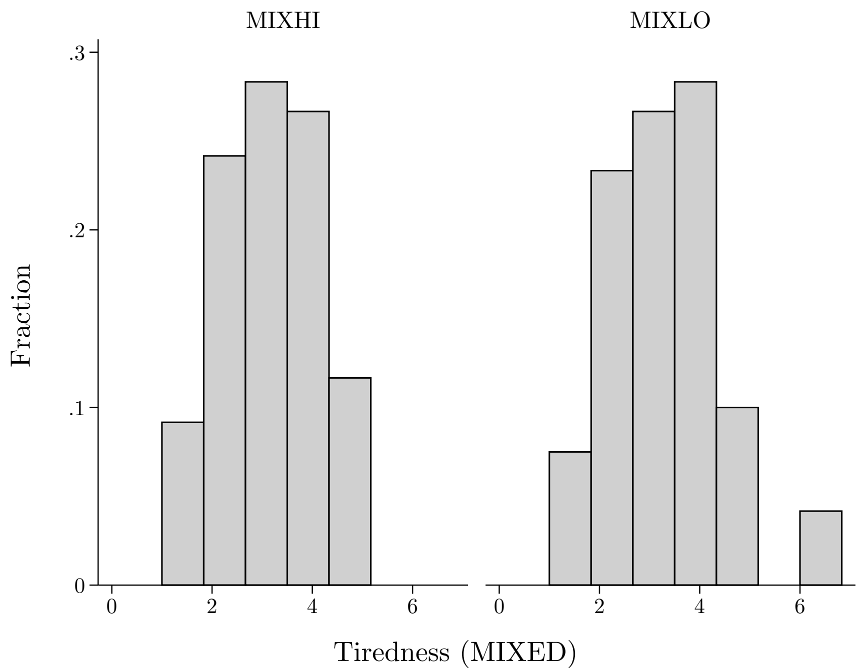


Figure 16: Tiredness in Treatment *MIXED* by Condition

Distribution of Subjective Measures (MIXED)

MIXHI	Mean	Standard deviation
Strain	2.625	1.1743
Tiredness	3.075	1.1607
MIXLO	**Mean**	**Standard deviation**
Strain	3.216	1.2379
Tiredness	3.225	1.2465

Table 16: Distribution of Subjective Measures (MIXED)

A.5 Distribution of Answers in the Cognitive Reflection Test

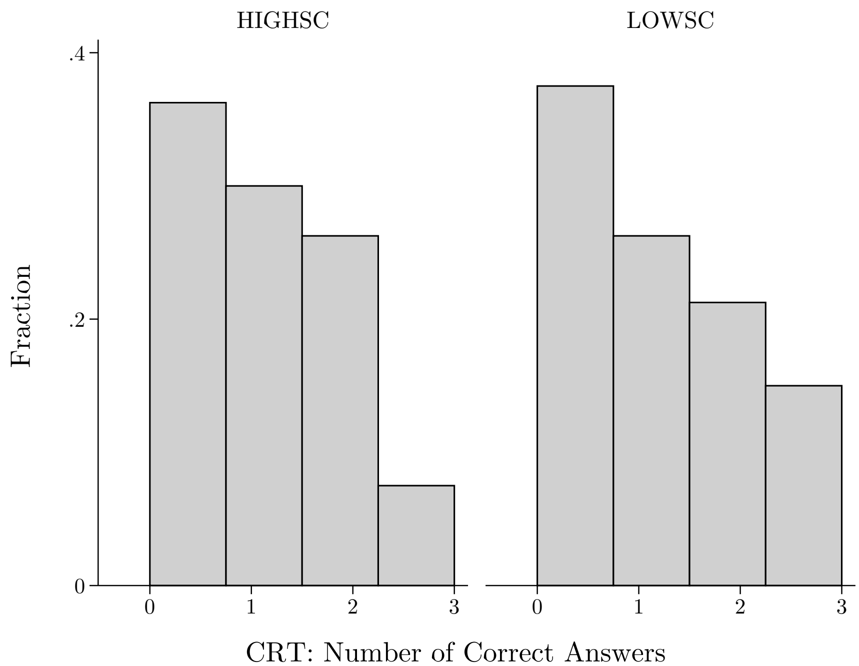


Figure 17: Correct CRT Answers in *HIGHSC* vs *LOWSC*

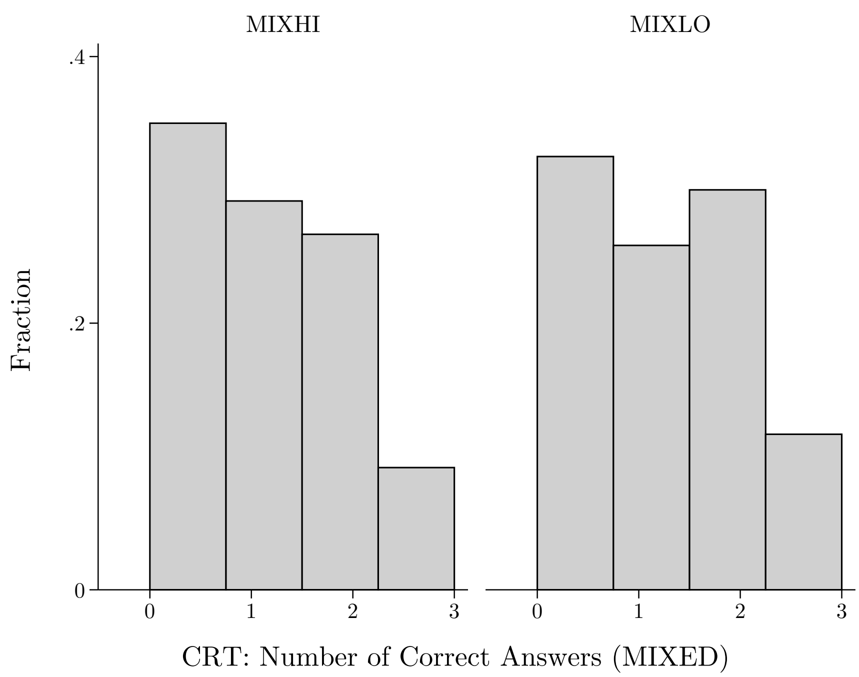


Figure 18: Correct CRT Answers in *MIXED* by condition

Distribution of Answers in the Cognitive Reflection Test

	Mean	Standard deviation
HIGHSC	1.05	0.9665284
LOWSC	1.1375	1.087836
MIXED	Mean	Standard deviation
MIXHI	1.1	0.990
MIXLO	1.2	1.028

Table 17: Distribution of Answers in the Cognitive Reflection Test

A.6 Distribution of Certainty Equivalents

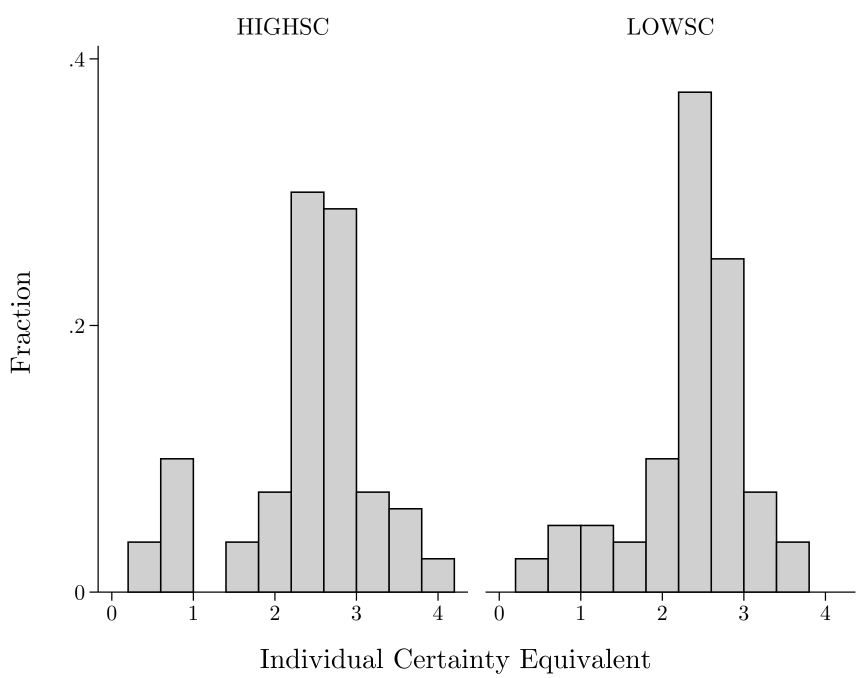


Figure 19: Individual Certainty Equivalents in *HIGHSC* vs *LOWSC*

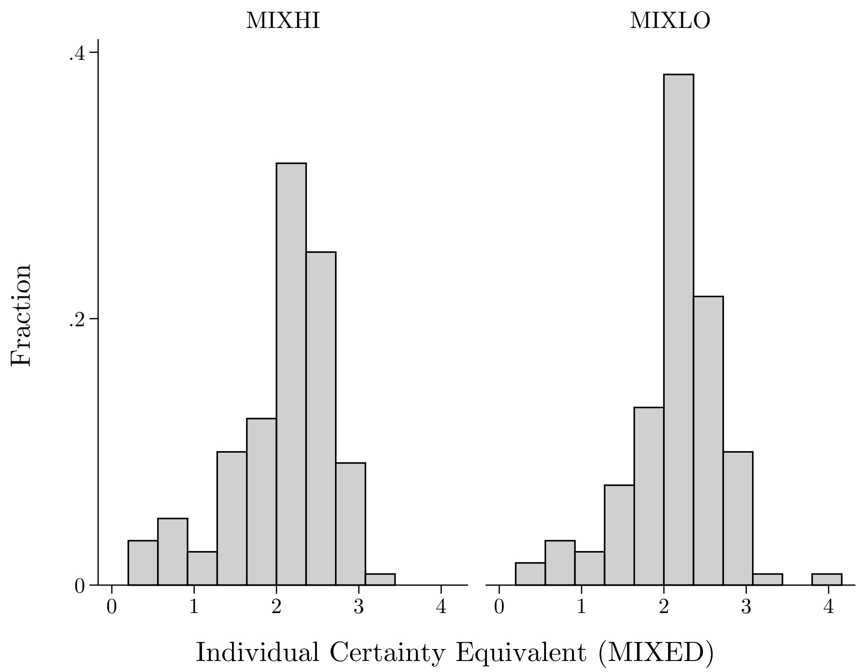


Figure 20: Individual Certainty Equivalents in *MIXED* by Condition

Distribution of Individual Certainty Equivalents

	Mean	Standard deviation
HIGHSC	2.2	.8467361
LOWSC	2.145	.6964467
MIXED	Mean	Standard deviation
MIXHI	2.08	.693
MIXLO	2.16	.625

Table 18: Distribution of Individual Certainty Equivalents

A.7 Instructions

A.7.1 Main Experiment

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

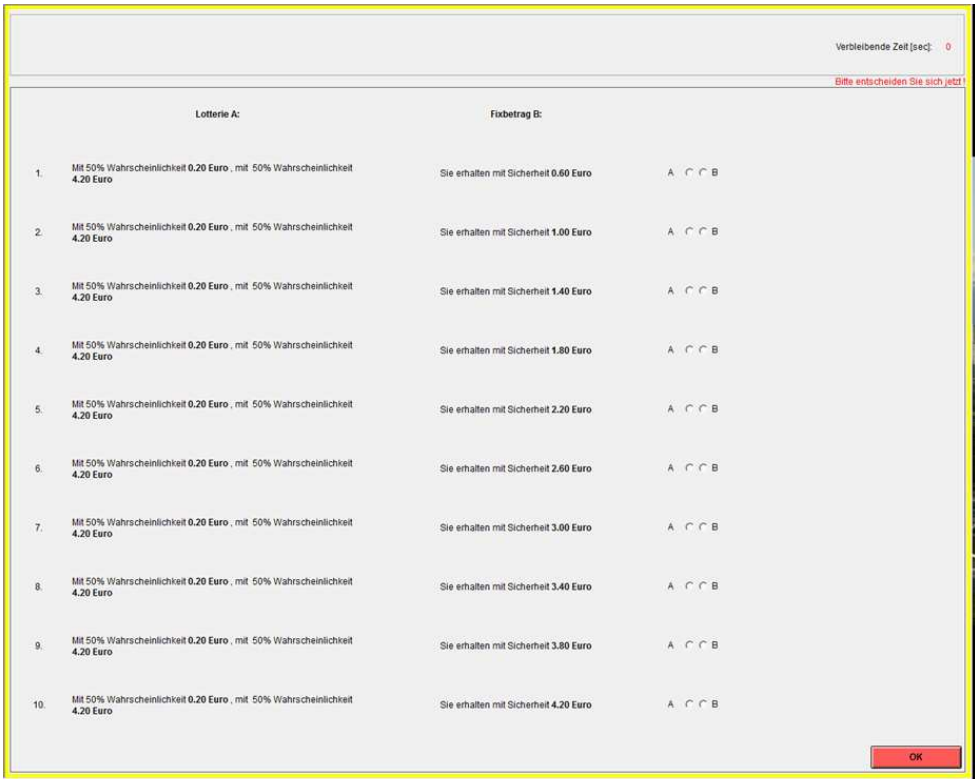
Task

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%).

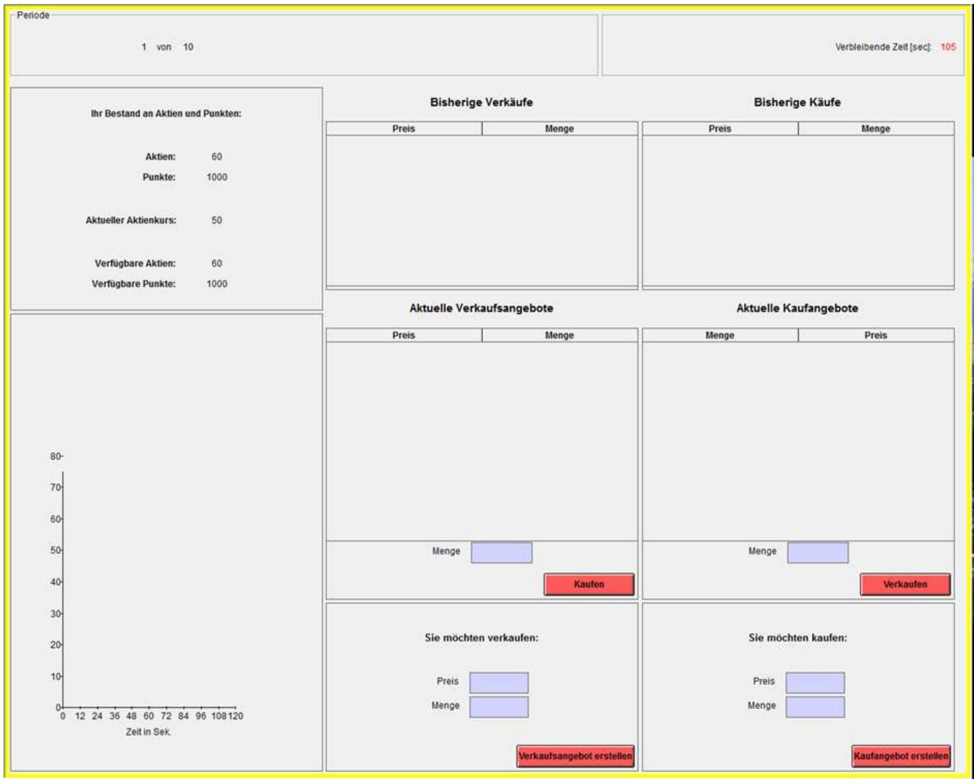
During the 2 minutes trading period you can either offer to sell or buy shares or accept existing buying or selling offers by other participants.

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.

A.7.2 Additional Experiment

Part I

Bezahlung In this part of the experiment, you can earn money, denominated in Taler. At the end of the experiment, we will convert Taler into Euros. The exchange rate will be:

500 Taler = 1 EUR (1 Taler = 0.002 EUR = 0.2 Cent)

Task

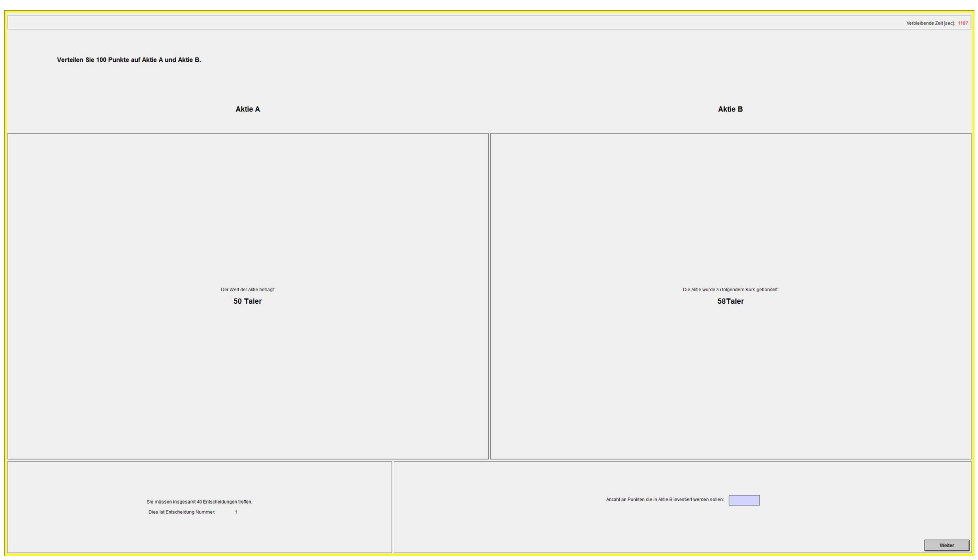
In part I you will have to decide to invest in two assets of fictitious firms. In all, you will face 20 such decisions.

You will receive 100 points for every decision that you can freely allocate between the two assets. You can choose any integer number, for example: 100:0, 28:72, 50:50, 68:32 or 0:100.

The assets you can choose from we will call asset A and asset B. Owning asset A gives you a certain, known payoff. The value of this asset will be shown to you in the lower left corner of your screen. This value can be different for every decision. The value of asset B is unknown to you. Instead, the right half of your screen will show you the average trading price of asset B in several markets. Also this price can be different for every decision. For every point you invest in asset A or B, you will receive the asset's value in Taler.

Example: Asset A comes with a certain payoff of 50 Taler. Asset B was traded for a price of 58 Taler, the actual value (that is unknown to you) of asset B was 60 Taler. You decide to invest 70 points in asset B (and therefore 30 points in asset A). Then you will receive for asset A 30 points x 50 Taler = 1,500 Taler. For asset B you will receive 60 Taler x 70 points = 4,200 Taler. Therefore, you will receive 5,700 Taler in total.

Here you can see an example screenshot:



Next to the two options asset A (left) and asset B (right) you will also see how many decisions you will still have to work on (bottom left corner). In the bottom right corner of your screen, you can enter the amount of points you wish to invest in asset B. The computer will automatically allocate the remaining points to asset A. Example: You wish to invest 25 points in asset B und 75 points in asset A. Then please enter 25 into the input field.

After you have finished entering the desired amount of points, click on the ‘next’ button to proceed to the next decision. If you have finished all 20 decision problems, this part will end automatically.

In the following you will find additional information regarding the trading price of asset B and the payoff from this part.

Detailed information: Trading price of asset B

The average trading price of asset B that you will see on the right hand side of your screen is the result from a previous experiment. It is the average price of 8 markets, in which 10 participants (in each market) could buy and sell the asset over 120 seconds. All participants were told about the expected value of the asset and all participants received the same information.

Although you do not know the real value of asset B, trading prices may contain information about the true value. Note, however, that the trading price can also be higher or lower than the true value, depending on the behavior of these experimental subjects.

Payoff At the end of this part, the computer will determine one of the 20 decision problems randomly and with equal probability to be payoff relevant. Your payoff consists of the number of points you have invested in asset A times the known value of asset B, plus the points you invested in asset B times the unknown value of asset B. This sum will then be paid to you according to the above mentioned exchange rate. At the end of the experiment, you will see your earning on a dedicated screen. In addition to your earnings from this experiment, you will receive 5 EUR for showing up on time.