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Information Aggregation and the Cognitive Make-up of Traders

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Abstract

We assess the effect of the cognitive make-up of traders on the informational efficiency of markets. We put forth that cognitive skills, such as cognitive reflection, are crucial for ensuring the informational efficiency of markets because they endow traders with the ability to infer others' information from prices. Using laboratory experiments, we show that information aggregation is significantly enhanced when (i) all traders possess high levels of cognitive sophistication and (ii) this high level of cognitive sophistication is common information for all traders. Our findings shed light on the cognitive and informational constraints underlying the efficient market hypothesis.

Keywords: Information aggregation, market efficiency, cognitive skills, cognitive finance, experimental finance.

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1. Information Aggregation in Experimental Asset Markets

The extent to which markets aggregate disperse information has been at the center of the heated debate on market efficiency in Finance (Fama, 1970; Shleifer, 2000; Thaler, 2005; Fama, 2008; Shiller, 2015). The empirical assessment of market efficiency is a daunting task because not only is it impossible for researchers to observe traders' private information, but it is also impossible to test market efficiency independent of a specific equilibrium model for asset prices (see, for example, Fama 1991).

An alternative approach to the archival studies of financial time series is to use experimental asset markets to assess information aggregation, which measures the market's ability to consolidate disperse information into clear price signals regarding the asset's true value. In this setting, the researcher not only has control over the distribution of private information but also knows the fundamental value of the traded asset. It follows that in an experimental asset market, informational efficiency can be tested separately from asset pricing models. This promising approach was pioneered by Plott and Sunder (1988) (PS, henceforth), who designed a laboratory environment to study information aggregation. We use one of their specific designs to analyze further the market's ability to aggregate disperse information by identifying the critical condition(s) under which aggregation occurs. This design introduces an experimental asset that can only assume one of three possible values, 50, 240 or 490. Each trader in the market is then informed of a possible value the asset cannot take. As half of the traders are given one signal (e.g., "Not 50") and the other half are given the other possible signal (e.g., "Not 240"), the aggregate information available to all traders in the market is complete. If markets aggregate information, then trading should only occur at the true asset value (e.g., 490). This prediction implies perfect information aggregation in the spirit of Fama's (1970) definition of strong-form efficiency according to which all private information should ultimately be incorporated into prices.

In PS, strong-form efficiency was motivated by the existence of a fully-revealing rational expectations equilibrium in which subjects' beliefs regarding the true asset value coincide with the true asset value. However, as first suggested by Grossman and Stiglitz (1980), this fully-revealing rational expectations equilibrium may not be attainable. Indeed, if all traders know that prices are fully revealing, they will not engage in the costly acquisition of information, which will prevent any aggregation of private information. In our experimental setup, private information is given to traders for free, thus somehow alleviating Grossman-Stiglitz concerns. Nevertheless, if we take into account any cognitive costs associated with trading based on information, then the reasoning of Grossman and Stiglitz (1980) implies that fully-revealing prices might not be achieved.

Despite the findings of PS showing evidence in favor of strong-form efficiency, several recent experimental studies, using various institutional designs, have cast doubt on the market's ability to aggregate dispersed private information (see, e.g., Biais et al. 2005; Hanson, Oprea and Porter 2006; Veiga and Vorsatz 2010; Huber, Angerer and Kirchler, 2011; Page and Siemroth, 2017; Corgnet et al. 2018; Page and Siemroth, 2018; Corgnet, DeSantis and Porter, 2019).

Limitations to the aggregation of private information have also been evidenced in the herding literature (Banerjee, 1992; Bikhchandani, Hirshleifer and Welch, 1992; Guarino, Harmgart and Huck, 2011), which shows that individuals making sequential decisions might rationally ignore their own private information to follow the majority's decision. When considering a financial setting in which a market maker sets quotes, Cipriani and Guarino (2005; 2009) provide experimental evidence supporting the theoretical prediction that herding would only occur in the presence of multidimensional uncertainty (Avery and Zemsky, 1998).

By contrast with previous market design research focusing on the institutional (e.g., PS; O'Brien and Srivastava, 1991) and informational features (Copeland and Friedman, 1987; Camerer and Weigelt 1991; Nöth and Weber, 2003; Plott, Wit and Yang, 2003; Barner, Feri and Plott, 2005) of markets, we study the impact of the cognitive make-up of traders on the aggregation of private information. Our approach is motivated by the observation that any fully-revealing rational expectations model crucially hinges upon traders' ability to unambiguously infer others' information from market orders (e.g., Guesnerie, 2005).[1] Given the extensive literature in cognitive psychology (e.g., Tversky and Kahneman, 1974; Kahneman, 2011) documenting the failures of individuals (including experts) to apply Bayesian inference adequately, the rationality assumption may have to be reassessed in the light of behavioral finance models (Daniel, Hirshleifer and Subrahmanyam, 1998, 2001; Hong and Stein, 1999; Shleifer, 2000; Hirshleifer, 2001; Kogan, 2009).

Following the work of Corgnet, DeSantis and Porter (2018) (henceforth, CDP), we highlight the crucial role of cognitive skills, which we assess using the cognitive reflection test (CRT, henceforth), for predicting one's ability to infer others' information from prices. The CRT has been shown to be an accurate measurement of standard cognitive skills (Frederick, 2005).[2] CRT questions are also commonly asked in *Wall Street* interviews for trading positions (Zhou, 2008; Crack, 2014), and not surprisingly, professional traders earn high scores on the CRT (Thoma et al. 2015).

We considered two hypotheses, which we subsequently tested with experimental asset markets. Both hypotheses focus on the cognitive sophistication of the traders in the market. We refer to traders with high cognitive skills as *sophisticated*.[3] Our first hypothesis suggests that a higher proportion of *sophisticated* traders in the market will improve information aggregation. This is the case because *sophisticated* traders, unlike *non-sophisticated* traders, can infer others' private information from market orders and thus learn the true asset value over the course of the market. Importantly, the ability

[1] We define the term "market order" to include bids, asks, and prices. We do not use it to differentiate between immediately executable orders and limit orders.
[2] Cognitive reflection scores positively correlate both with standard intelligence tests scores as well as with one's need for cognition (see Frederick, 2005; Thomson and Oppenheimer, 2016) which is defined as a person's tendency to enjoy and engage in effortful thought (Cacioppo and Petty, 1982).
[3] In CDP (*non-*) *sophisticated* traders were referred to as (*non-*) *reflective* traders. Here we use the term *sophisticated* to emphasize the notion that we are using cognitive reflection as a proxy for cognitive sophistication.

of *sophisticated* traders to learn the true asset value relies upon their knowledge of the proportion of *sophisticated* traders populating the market. For example, if *sophisticated* traders wrongly believe that a large proportion of subjects are making trading decisions based solely on their private information, then they will downplay the informational content of asset prices, which will limit the degree of information aggregation in the market. Furthermore, *sophisticated* traders will only be able to correctly extract private information from market orders when the proportion of *sophisticated* traders is commonly known by all *sophisticated* traders. Our second hypothesis thus posits that information aggregation can only be successful if the high level of traders' cognitive sophistication is *common information*.[4] This second hypothesis emphasizes that the conditions for information aggregation are especially restrictive.

We tested our two hypotheses by recruiting *sophisticated* subjects, which we define as those individuals whose CRT score, i.e. the number of correctly answered questions, ranked in the top 20% of all scores in the subject pool of the lab at which the study was conducted. These subjects were highly sophisticated, as evidenced by the fact that their average CRT scores were similar to those of professional traders (see Thoma et al. 2015). We compared the results of experiments which were conducted with solely *sophisticated* traders to baseline experiments in which we did not utilize the CRT score as a recruitment criterion. Consistent with our first hypothesis, we show that the recruitment of *sophisticated* individuals (without informing them of their fellow traders' high level of cognitive sophistication) led to asset prices that were closer to the true asset value than in our baseline sessions.

[4] We state our hypothesis in terms of *common information* rather than common knowledge because of the impossibility to convincingly induce common knowledge in our market experiments. Instead, we will induce *common information* of the proportion of *sophisticated* traders by informing all subjects in the experiment of other traders' levels of cognitive sophistication.

In line with our second hypothesis, information aggregation was significantly enhanced (i.e., prices significantly closer to the true asset value) when the highly *sophisticated* traders populating the market were aware of each other's high level of *sophistication*.

2. Experimental Design

2.1. Asset markets

Our study uses the design of PS and, in particular, their parameterization of *Market 9* (Treatment C). Specifically, this design introduces an experimental asset that can only take three possible values: 50, 240 or 490 francs (each franc was worth $0.001) with probabilities 35%, 45% and 20%, respectively.[5] Each of the twelve traders in the market was privately informed of a possible value the asset could not take. Moreover, traders were informed that half of the traders were given one signal (e.g., "Not 50") and the other half were given the other possible signal (e.g., "Not 240"). Thus, the aggregate information available to traders in the market was complete so that prices could, in principle, reflect the true asset value (e.g., 490). The convergence of prices to the true asset value in this design constitutes the primary evidence of information aggregation in experimental asset markets. We chose this design as it allows for the study of the aggregation of disperse pieces of private information and thus requires, unlike markets with insiders (Plott and Sunder, 1982; Corgnet, DeSantis and Porter, 2019), all traders to infer others' private information from observing market orders in order to learn the true asset value.

2.2. Procedures

We conducted a total of 25 sessions with 12 traders in each.[6] Each session consisted of 17 markets with independent draws for the asset value. In the ten baseline sessions, traders were endowed with

[5] The exchange rate was chosen so that average subjects' earnings for the experiment were similar to average payments for a three-hour experiment at the lab where the study was conducted (i.e., average subjects' earnings were $46.45).
[6] These traders were inexperienced in that they did not have prior experience in similar laboratory market experiments.

1,200 francs in cash and four shares of the asset at the beginning of each market (baseline sessions). To test our cognitive sophistication hypotheses, we conducted two high-CRT treatments – one with common information of traders' sophistication and the other without common information. Four sessions of each high-CRT treatment were conducted using the same parameters as the baseline sessions. We also conducted two robustness treatments. The first of these treatments (Loan) was intended to ensure that any lack of information aggregation could not easily be explained by liquidity constraints. In these two sessions, each subject's cash endowment thus consisted of a 25,000 franc loan. The second robustness treatment (High Stakes) was designed to ensure that any lack of information aggregation could not easily be explained by insufficient incentives.[7] In these five additional High Stakes sessions we doubled the average payoffs ($86.3) earned by subjects in the experiments by endowing them with 2,400 francs and four shares while also doubling the asset values (see Table 1 for a description of the treatments).

Table 1. Summary of the experimental design.

Treatment	*Number of traders*	*Number of markets* (market length in minutes) -Sessions-	*Endowment* / Loan Francs (Assets)	*Asset values* Francs (Probabilities)	*Trading mechanism*
Baseline	12	17 (5) - 10 -	1,200 (4)	50, 240, 490 (0.35,0.45,0.20)	Computerized continuous double auction
High CRT (*No common information*)	Same	17 (5) - 4 -	Same	Same	Same
High CRT (*Common information*)	Same	17 (5) - 4 -	Same	Same	Same
Loan	Same	17 (5) - 2 -	25,000 Loan (4)	Same	Same
High Stakes	Same	17 (5) - 5 -	2,400 (4)	100, 480, 980 (0.35,0.45,0.20)	Same

[7] This instructions utilized in this treatment were also modified to facilitate readability. Refer to Appendix B for a listing of the modifications to the original baseline instructions.

Before the trading phase of each session, subjects completed a training exercise regarding a random device (a spinning wheel) that represented the probabilistic distribution of the asset value (50, 240 or 490 francs) at the end of each market (see Appendix B). They were also instructed on how to use the trading software utilized in the experiment and completed a 7-question comprehension quiz on the mechanics of the market (see Appendix B).

2.3. End-of-session tests

At the end of each session, subjects completed a (computerized) series of tests and a demographic survey (see Appendix C). Subjects received a $3 payment for the completion of these tests.[8] In particular, we chose to administer the CRT, which has been found to correlate with trading behavior in related market experiments (see, for example, Noussair, Tucker and Xu, 2014; Corgnet et al. 2015; CDP; Kocher, Lucks and Schindler, 2018).

3. Cognitive Skills and Information Aggregation

3.1. Hypotheses

Given the findings of Biais et al. (2005) and CDP, the common assumption that all traders are homogenous and sophisticated (e.g., Kihlstrom and Mirman, 1975) and therefore have the ability to learn from market orders, is questionable. Instead, we consider the case in which *sophisticated* as well as *non-sophisticated* traders populate markets.

Sophisticated traders who are able to use market orders to update their own beliefs about the true asset value should ultimately be better informed than the trader who does not learn from market orders.[9] Thus, traders who use market orders to update their beliefs should trade more consistently with the true asset value than those who disregard market orders as a signal of the true asset value

[8] As is common practice in the literature, a pay-for-performance incentive scheme was not used for these tests.
[9] This is the case as long as all other traders are not trading randomly.

(see Corgnet, DeSantis and Porter, 2019 for a model). In particular, CDP show that cognitive skills, as measured by cognitive reflection, explain a trader's inclination to trade *consistently* with the true asset value, where a *consistent* trade is one that implies buying (selling) the asset for a price below (above) the true asset value. We illustrate this finding in Table 2.

Table 2. Trading *consistently* with the true asset value for all individual-level data across CRT scores.+

CRT scores		0-1	2-3	4-5	6-7
Proportion of *consistent* trades	Average	53.6%	56.8%	57.6%	62.1%
	Median	50.0%	60.0%	60.0%	70.0%
Proportion of subjects		35.0%	35.0%	20.8%	9.2%

+Baseline data were used.

Because traders possessing high cognitive skills are better able to learn the true asset value in markets with private information than those who do not, they will also tend to obtain higher earnings. *Non-sophisticated* traders would typically not learn others' private information over the course of the market because they fail to infer others' signals from market orders. This behavior of *non-sophisticated* traders is in line with the prior information or Walrasian model (Lintner, 1969), according to which traders make decisions based solely on their private information. Experimental evidence for such behavior has also been reported in Kogan (2009) who showed that traders tend to downplay the informativeness of prices as accurate signals of other traders' private information.

Individuals' cognitive reflection is also closely related to their ability to correctly apply Bayes' rule and refrain from using simple heuristics. Recent works have shown that CRT is the cognitive test that best predicts an individual's capacity to apply Bayes' rule adequately (Toplak, West and Stanovich, 2011) and avoid known heuristics and behavioral biases (e.g., Cokely and Kelley, 2009; Oechssler, Roider and Schmitz, 2009; Campitelli and Labollita, 2010; Toplak, West and Stanovich, 2011). In sum, cognitive skills, as measured with CRT, favor accurate Bayesian updating, thus facilitating one's inference of other's information via market orders. We thus posit the following hypothesis.

Hypothesis 1. *As the proportion of sophisticated traders in the market increases, market prices will be closer to the true asset value.*

The intuition supporting Hypothesis 1 follows from the fact that an increase in the proportion of *sophisticated* traders in the market will increase the informational content of market orders. *Sophisticated* traders will be able to infer others' information by observing market orders and will subsequently trade based on their updated beliefs of the asset value. These subsequent trades will transmit information to the market, leading prices to reflect the aggregate information. As a result of this increase in the number of informed orders, asset prices will more likely reflect traders' available information.

There exists, however, one issue with this argument. *Sophisticated* traders will only make use of market orders as accurate signals of the true asset value if they believe that market orders are set by *sophisticated* individuals who trade based on updated information regarding the true asset value. If *sophisticated* traders believe that a large proportion of individuals are not trading based on updated information (*non-sophisticated* traders), then they will downplay market orders as accurate signals of the true asset value. This, in turn, will ultimately hinder information aggregation. This leads to our second hypothesis, which establishes the essential role *common information* of traders' cognitive sophistication (i.e., all traders are informed of the proportion of *sophisticated* traders in the market) serves in enabling markets to aggregate information.

Hypothesis 2. *In a market populated solely by sophisticated traders, prices will be closest to the true asset value when the cognitive make-up of traders is common information.*

Although Hypothesis 2 focuses on the case in which all traders are *sophisticated*, our reasoning can be applied to markets populated by a mix of *sophisticated* and *non-sophisticated* traders. Indeed, as traders know the cognitive make-up of other traders in the market, their inference about others' private information will be more accurate, thus fostering informational efficiency in markets. For example, if you are the only *sophisticated* trader in the market but mistakenly believe others are also *sophisticated,* you will infer incorrect information from prices, thus lowering the informational content of your trades and the informational efficiency of the market.

To test our hypotheses regarding the causal effect of traders' cognitive skills on the informational efficiency of markets, we need to be able to exogenously manipulate the proportion of *sophisticated* traders in the market. We also require a measure of traders' *cognitive* skills. As the CRT is a key determinant of an individual's capacity to properly use Bayes' rule, it is an appropriate measure of a trader's ability to infer other traders' information from market orders.[10] We thus chose CRT as our primary measure of cognitive sophistication.[11] Consistent with CDP, we define a *sophisticated* (*non-sophisticated*) trader as one who scores in the top (bottom) 20% on the CRT.

Because CRT and standard intelligence test scores exhibit a substantial positive correlation ranging from 0.2 to 0.4 depending on the study (see Frederick, 2005; Toplak, West and Stanovich, 2011; Corgnet, Hernan and Mateo, 2015; Stanovich, West and Toplak, 2016), it would seem reasonable to expect similar results when using alternative cognitive tests, such as Raven, instead of CRT to recruit *sophisticated* traders.

3.2. Recruiting on CRT

To recruit by CRT scores, we used the results of an extensive survey conducted at our home institution at the beginning of the academic year in which our experiments were conducted. All of the subjects registered in the laboratory's database (n = 1,963) were invited to complete a comprehensive one-hour survey which included the extended, 7-item CRT developed by Toplak, West and Stanovich

[10] Interestingly, CDP show that Raven test scores, which is a common measurement of cognitive sopthistication, do not correlate with Bayesian updating performance.

[11] CDP also show that, on average, high-CRT individuals earn more than low-CRT individuals. This is in line with a series of experimental works in the experimental asset market literature (Noussair, Tucker and Xu, 2014; Corgnet et al. 2015; Kocher, Lucks and Schindler, 2018) that have shown that high-CRT subjects outperform low-CRT subjects.

(2014) as well as the Raven test (Raven, 1936) (see Appendix C).[12,13] The use of the new CRT items developed by Toplak, West and Stanovich (2014) was motivated by concerns regarding previous exposure to Frederick's (2005) three original questions (see Stieger and Reips, 2016). Note that the lab survey was the first instance in which CRT scores were collected at the lab where the study was conducted so that subjects were unlikely to be familiar with the test. This is confirmed by the fact that the average 3-item CRT score (1.18) of the subjects who participated in the beginning-of-year survey is remarkably similar to that of the original sample of Frederick (2005) with 3,428 students (1.24). It is also reassuring that, in the beginning-of-year survey, the correlation coefficient between the 7-item CRT scores and IQ scores measured using the Raven test ($\rho = 0.34$, p-value < 0.001) is very similar to the coefficient estimated in prior studies (see e.g., Toplak, West and Stanovich, 2011).[14]

Using the 7-item CRT, we recruited subjects in the top 20% of the distribution of scores of the 885 students who participated in the survey but not in any prior experimental asset market experiments similar to the PS design.[15] We thus recruited subjects who scored 5, 6 or 7 on the 7-item CRT (see Table A1 in Appendix A for the distribution of the 7-item CRT scores in the student population). This subset of our population has an average score of 2.65 on the original 3-item CRT, which places them in the top 20% of the distribution of the original CRT scores of 3,428 students surveyed in Frederick (2005). The scores of our high-CRT subjects were significantly higher than the CRT scores of 592 US individual traders who averaged 1.28 (see Krische, 2015) and professional workers in the Finance and Banking sectors with an average score of 1.62 (see Thoma et al. 2015). The only groups that match the CRT scores of our top 20% sample are the 102 professional traders surveyed in Thoma et

[12] See CDP for a detailed description of the measures used in the survey.

[13] The questions in Frederick's (2005) original 3-item CRT are a subset of the questions posed in the 7-item CRT of Toplak, West and Stanovich (2014).

[14] The authors report a correlation coefficient between different measures of fluid intelligence and CRT scores. The correlation coefficient between CRT scores and the Wechsler Abbreviated Scale of Intelligence (Wechsler, 1999) [working memory, Gronwall, 1977] is 0.32 [0.33].

[15] Experiments involving only subjects with high cognitive skills have been conducted in a few recent studies (e.g., Gill and Prowse, 2016; Bosch, Meissner and Bosch-Domenech, 2018).

al. (2015) and the 24 Caltech students who participated in the study of Brocas et al. (2014) (see Figure 1 for a summary of 3-item CRT scores across a wide range of samples).

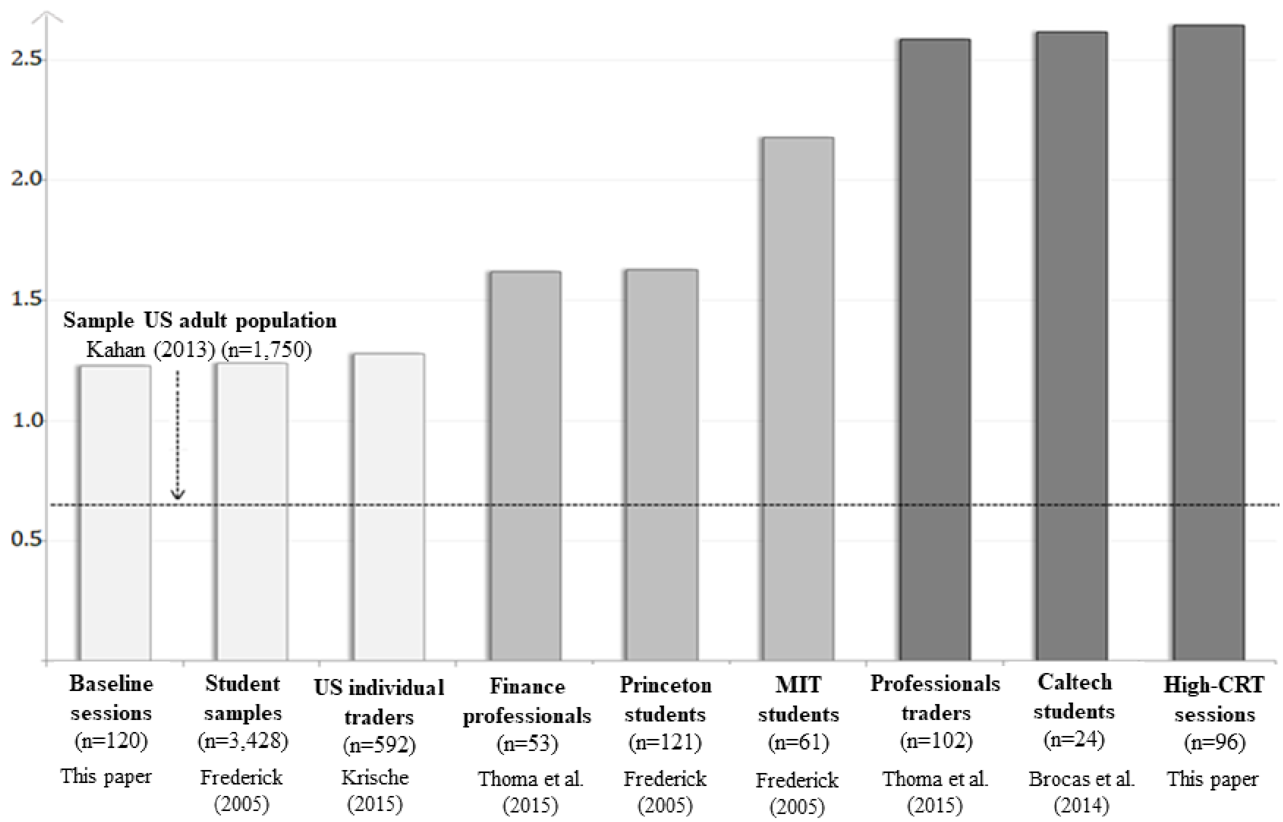

Figure 1. Average 3-item CRT scores for a wide range of samples.[16]

To test Hypotheses 1 and 2, we conducted two treatments: one in which traders were informed that all market participants scored in the top 20% of the student population *(common information* treatment) and one in which they were not informed (*no common information* treatment). In the *common information* treatment, traders were informed that "the people who were recruited for today's experiment have all previously taken a cognitive test [which was described in the instructions] and have all obtained a very high score (in the top 20% of a population of 1,000 students registered at the lab where the study was conducted)" (see instructions in Appendix B). The difference across

[16] Sinayev and Peters (2015) also suggest that the average three-item CRT is below 1 in the general US population (n = 2,703).

treatments may appear to be particularly subtle. However, research in social psychology has shown that people are especially attentive to any information on their skills and on their relative standing in the population (e.g., Festinger, 1954). This suggests our experimental manipulation is likely to be salient.

The *common information* treatment is one in which the behavioral type of other traders is revealed thus facilitating traders' inference regarding the private information contained in market orders. Our *common information* treatment can be seen as a mechanism by which the experimenter 'injects' traders with emotional intelligence by facilitating their own understanding of other traders' strategies. Emotional intelligence, which consists of the capacity to read other traders' intentions and is often referred to as theory of mind (see e.g., Bruguier, Quartz and Bossaerts, 2010; Hefti, Heinke and Schneider, 2016; Fe and Gill, 2018; Kimbrough, Robalino and Robson, 2017; Bossaerts, Suzuki and O'Doherty, 2019 for economic applications), has been identified by CDP (along with fluid intelligence and cognitive reflection) as a key driver of traders' earnings in information aggregation experiments. The reason we focus on CRT instead of theory of mind skills in the current study is that it allows us to separate the effect of *common information* regarding traders' cognitive skills on the informational efficiency of markets from the effect of these cognitive skills. This might not have been possible if we had selected traders based on theory of mind scores as traders possessing high theory of mind may have rapidly inferred other traders' behavioral types even in the absence of *common information* of traders' scores. In that case, the *common information* and the *no common information* treatments would lead to similar levels of informational efficiency.

We conducted four sessions per treatment with a total of 96 subjects.[17] As intended, the CRT scores of the high-CRT sessions were significantly higher than for the baseline sessions (all p-values < 0.001,

[17] Given our limited pool of high-CRT subjects (177), our (intended) target number of sessions per treatment was exactly equal to four.

Wilcoxon Rank Sum tests, WRS henceforth) (see Table 3). There are no significant differences in CRT scores between the high-CRT sessions with and without *common information* (p-value < 0.873, WRS).

Table 3. 7-item CRT scores by treatment.

Treatment	Average (median) -Stand. Dev- CRT score
Baseline (n = 120)	3.31 (3.00) -1.86-
High CRT (n = 48) (*No common information*)	5.70 (6.00) -0.94-
High CRT (n = 48) (*Common information*)	5.72 (6.00) -0.80-

4. Results

We observe graphically in Figure 2 that average prices for the baseline sessions differ dramatically from the true asset value.[18,19] It is also clear from Figure 2 that the high-CRT sessions led to prices that were closer to the true asset value than the baseline sessions. This observation is in line with Hypothesis 1. Consistent with Hypothesis 2, we observe that average prices are closest to the true asset value for the high-CRT sessions with *common information*.[20]

[18] See Appendix D for graphs of average prices for each session separately, including the Loan and High Stakes sessions.
[19] These findings appear at odds with PS who report prices close to the true asset value. However, our work is not a direct replication of the authors' findings because it differs in a number of important ways from PS such as the use of computerized instead of oral auctions. The reader can refer to Corgnet et al. (2019) for a replication study of PS.
[20] In addition to Figure 2, we direct the reader to video links showing examples of the differences in information aggregation across treatments. In the following links, one can replay Market 17 (last market of the experiment where the true asset value is 490) for one baseline session, one high-CRT session without *common information* and one high-CRT session with *common information*:
(https://sites.google.com/site/financecognitive/videos).

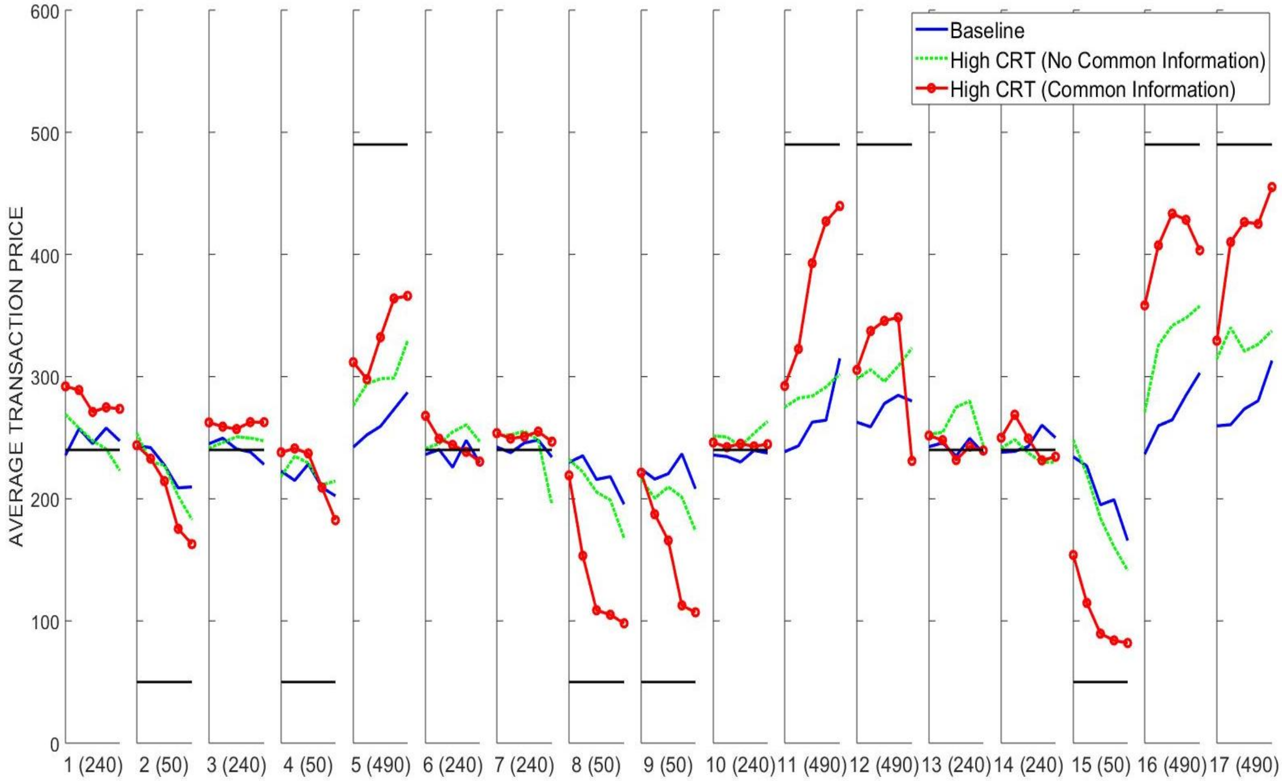

Figure 2. Average price per minute over the four high-CRT with *common information* (solid red lines with circle markers), the four high-CRT without *common information* (dotted green lines), and the 10 baseline (solid blue lines) sessions for each of the 17 markets. The true asset value is denoted at the bottom of each subfigure, i.e., 50, 240 and 490, and also represented by a solid black horizontal line.

To assess information aggregation, we report the average across sessions of the mean absolute deviation (MAD) between the price and the true asset value in Table 4.[21] For each session, this value is calculated as:

$$MAD := \underset{i}{\text{average}}|p_i - v|$$

where i represents a transaction, p_i corresponds to the transaction price, and v is the true asset value. Taking our cue from PS, we give information aggregation its "best chance" by considering the last occurrence of each of the possible asset values: 50, 240 and 490 (i.e., markets 15, 14 and 17, respectively).

[21] The MAD measures per session are detailed in Table A2 in Appendix A.

In Table 4, we provide support for our hypotheses by reporting the mean absolute deviations with respect to the true asset value for each treatment. Extending the analyses conducted in PS, we compute this variable for all transactions, column (1), as well as for the last three transactions, column (2), in markets 14, 15 and 17.

In line with Hypothesis 1, we show that the mean absolute deviation is significantly smaller in the high-CRT sessions than in the baseline sessions whether we consider traders' level of *sophistication* to be *common information* (p-value = 0.005 for all transactions as well as for the last three transactions, WRS) or not (p-value = 0.005 for all transactions and p-value = 0.157 for the last three transactions, WRS). These results are confirmed when conducting panel regression analyses using MAD values for each market in each session of each treatment as the dependent variable (see Tables A3 and A4 in Appendix A).

Table 4. Comparison of mean absolute deviations by treatment for (1) all transactions and for (2) the last three transactions in markets 14, 15 and 17.

	Mean Absolute Deviation	
Treatments	(1) All transactions	(2) Last 3 transactions
Baseline	131.28	115.78
High CRT (*No common information*)	106.71	90.08
High CRT (*Common information*)	59.89	28.28
Loan	216.93	226.67
High Stakes	142.37	121.52

In line with Hypothesis 2, prices are closer to the true asset value in the high-CRT sessions with *common information* than in the high-CRT sessions without *common information* (p-value = 0.043 for the last three transactions and p-value = 0.083 for all transactions, WRS). These non-parametric tests used only four independent MAD values per treatment. Unsurprisingly, panel regression analyses which use MAD values for a single market instead of for a single session, report differences between treatments that are statistically significant at even lower levels (see Table 5).

Table 5. Mean absolute deviation in the high-CRT sessions.

This table presents the results of linear panel regressions with random effects and robust standard errors (in parentheses) clustered at the session level. The mean absolute deviation from the true asset value in a market is used as the dependent variable. All high-CRT sessions are used. The treatment dummy "CRT Common Information" takes value one if a market belongs to the high-CRT treatment with *common information* and value zero otherwise.

Dependent Variable	Sample (Markets / Transactions)			
MAD	Markets 14, 15 & 17 All transactions (1)	Markets 14, 15 & 17 Last 3 transactions (2)	All markets All transactions (3)	All markets Last 3 transactions (4)
Constant	-716.172*** (138.451)	-440.769*** (160.834)	83.400*** (14.049)	97.381*** (12.990)
Treatment Dummy "CRT Common Information"	-49.320*** (18.105)	-61.806*** (21.026)	-39.417*** (16.226)	-25.009* (12.896)
True Asset Value	-0.201** (0.078)	-0.103 (0.068)	0.087* (0.046)	0.071*** (0.025)
Market Number	57.406*** (10.120)	36.372*** (11.497)	-1.240 (0.900)	-0.500 (1.056)
Number of Observations	24	24	136	136
R^2	0.676	0.511	0.101	0.047
Prob > χ^2	0.000	0.001	0.012	0.000

*** Significant at the 0.01 level; ** at the 0.05 level; * at the 0.1 level.

We executed two robustness tests. To ensure our results were not due to the particular cash endowment, we ran two Loan sessions in which traders were given a 25,000 franc loan at the beginning of each market. The loan was repaid at the end of each market. To ensure the stakes for our experimental subjects were sufficient, we also ran five High Stakes sessions in which we doubled subjects' cash endowments (2,400 francs) as well as the true asset values (100, 480, 980) from the baseline. All other parameters in both robustness treatments were the same as the baseline. Average prices per minute are displayed in Figure A1 in Appendix A. As is shown in Table 4, prices were not significantly closer to the true asset value in either treatment than they were in the baseline. We report MAD values per session in Table A2 in Appendix A. MAD values were higher in the Loan and High Stakes treatments than in the baseline. This difference is significant when comparing the Loan treatment and the baseline (p-value = 0.032 for the last three transactions and for all transactions, WRS) and fails to reach significance when comparing the High Stakes treatment and the baseline (p-value = 0.806 for the last three transactions and p-value = 0.111 for all transactions, WRS). Similar results are obtained with panel regressions (see Tables A5 and A6 in Appendix A). Given the tendency of an influx of cash to boost prices in asset markets (Caginalp, Porter and Smith, 1998; 2001), it is not surprising that the deviations from true asset value were even larger for our Loan treatment than for our baseline sessions. Because the Loan and High Stakes treatments tend to produce even higher levels of mispricing than the baseline, the differences between high-CRT sessions and all sessions involving individuals with standard levels of CRT (i.e., baseline, Loan and High Stakes treatments) are highly significant (see Tables A7 and A8 in Appendix A).

Our findings show that inducing *common information* regarding traders' level of cognitive sophistication is essential for information aggregation. To our knowledge, this result has never been shown. In a related work, Forsythe and Lundholm (1990) study information aggregation in two-day laboratory experiments in which subjects participated in the same experimental asset market with the same traders on two consecutive days. In contrast to our setting, the authors consider the PS design in which the asset value differs across traders. In that context, they show that *common information* regarding payoffs is a necessary but not sufficient condition for information aggregation. They also note that information aggregation requires conducting the same experiment on consecutive days with the same subjects. Their study focuses on the common knowledge of payoffs leaving aside the issue of the common knowledge of traders' cognitive types. Thus, while related, their study is markedly different from ours.[22]

[22] Bringing subjects back the next day to participate in the same experiment with the same individuals can have many different effects which are difficult to tease apart. Between the two sessions, subjects may search for information about the experiment. Subjects may also share their experience with other subjects in the same session. This is especially the case for their study as markets were conducted orally. Additionally, demand effects may arise as subjects are called for a second day to do the exact same experiment as in the first day suggesting the experimenter may look for improved

5. Conclusion

We tested two hypotheses regarding the impact of traders' cognitive sophistication on the informational efficiency of markets. First, a higher proportion of *sophisticated* traders in the market should lead to prices that reflect the true asset value more closely. Second, prices will more closely reflect the true asset value if it is *common information* that all traders populating the market are *sophisticated*. The first hypothesis echoes the remark of Radner (1982) regarding the unrealistic cognitive demands of rational expectation models, whereas the second hypothesis is reminiscent of the work of Guesnerie (2005), which emphasizes the decisive role of common knowledge of rationality in rational-expectation models.

We tested these hypotheses by recruiting *sophisticated* individuals defined as having scored in the top 20% of all individuals in our subjects database on the CRT. Consistent with our first hypothesis, we show that recruiting *sophisticated* individuals led to asset prices that more accurately reflected the true asset value. In line with our second hypothesis, information aggregation was significantly enhanced when the *sophisticated* traders populating the market were aware of each other's high level of *sophistication*. To our knowledge, this is the first time *common information* about traders' cognitive sophistication (measured using CRT scores) has been shown to improve the aggregation of private information in markets. Our work implies that the informational efficiency of markets depends on both the composition of the traders in the market as well as what is commonly known about this composition.

Finally, our work extends previous market design research by exploring the cognitive constraints of the aggregation of dispersed information instead of focusing on institutional and informational features of markets. A natural step forward would be to incorporate cognitive constraints in the study

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subjects' performance. Finally, subjects may have time to reflect on the optimal strategy to adopt during the experiment. In contrast to our design, none of these effects seem to induce *common information* of cognitive sophistication.

of these features at both the empirical and theoretical levels. An interesting avenue of future research could, for example, study information aggregation in the presence of complex assets (e.g., Carlin and Manso, 2011; Carlin, Kogan and Lowery, 2013).

6. References

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7. Appendices

Appendix A. Tables and figures

Table A1. Distribution of 7-item CRT scores for the 885 students in the subject database who took the survey.

CRT score	% of students
0	12.77
1	19.32
2	18.42
3	14.01
4	13.33
5	9.83
6	7.23
7	5.08

Table A2. Comparison of actual prices to true value at the end of each market. Markets 14, 15 and 17 are considered.[+]

		MAD values	
Treatment	Session	All transactions	Last 3 transactions
Baseline	1	136.33	124.78
	2	122.76	132.33
	3	121.92	66.89
	4	118.37	84.56
	5	145.85	96.67
	6	150.10	134.00
	7	142.26	122.78
	8	115.93	140.33
	9	117.45	120.22
	10	141.86	135.22
High CRT *(No common information)*	11	128.73	127.33
	12	106.53	99.56
	13	106.72	81.22
	14	84.86	52.22
High CRT (*Common Information*)	15	72.16	47.00
	16	20.33	2.00
	17	85.80	57.78
	18	61.26	6.33
Loan	19	229.14	237.78
	20	204.72	215.56
High Stakes	21	125.81	104.22
	22	136.93	127.56
	23	145.56	137.56
	24	148.01	110.56
	25	155.53	127.72
Baseline, Loan and High Stakes average		144.62	130.51
High CRT average		83.30	59.18

[+]To facilitate comparison across sessions, the MAD values for the High Stakes sessions have been divided by two.

Table A3. Mean absolute deviation comparison between baseline and high-CRT sessions with *common information*.

Dependent Variable	Sample (Market / Transactions)			
MAD	Markets 14, 15 & 17 All transactions (1)	Markets 14, 15 & 17 Last 3 transactions (2)	All markets All transactions (3)	All markets Last 3 transactions (4)
Constant	-920.348*** (113.130)	-635.087*** (129.274)	92.264*** (15.638)	78.132*** (15.985)
Treatment Dummy "CRT Common Information"[23]	-73.790*** (14.184)	-87.500*** (15.404)	-44.832*** (11.307)	-56.132*** (14.572)
True Asset Value	-0.218*** (0.056)	-0.149* (0.078)	0.122*** (0.042)	0.102** (0.049)
Market Number	72.601*** (7.864)	51.504*** (9.004)	0.796 (0.716)	0.781 (0.778)
Number of Observations	42	42	238	238
R^2	0.773	0.538	0.116	0.131
Prob > χ^2	0.000	0.000	0.000	0.000

[23] The treatment dummy "CRT Common Information" takes value one if a market belongs to the high-CRT treatment with *common information* and value zero otherwise.

Table A4. Mean absolute deviation comparison between baseline and high-CRT sessions without *common information*.

Dependent Variable	Sample (Market / Transactions)			
MAD	Markets 14, 15 & 17 All transactions (1)	Markets 14, 15 & 17 Last 3 transactions (2)	All markets All transactions (3)	All markets Last 3 transactions (4)
Constant	-1,077.057*** (68.996)	-819.362*** (91.594)	82.263*** (13.190)	66.574*** (14.449)
Treatment Dummy "CRT No Common Information"[24]	-24.469** (10.747)	-25.694 (16.751)	-19.823*** (7.162)	-16.717* (10.564)
True Asset Value	-0.294*** (0.050)	-0.174** (0.081)	0.119*** (0.042)	0.112** (0.051)
Market Number	84.113*** (4.621)	63.934*** (6.643)	2.004*** (0.327)	1.757*** (0.478)
Number of Observations	42	42	238	238
R^2	0.818	0.558	0.093	0.084
Prob > χ^2	0.000	0.000	0.000	0.000

[24] The treatment dummy "CRT No Common Information" takes value one if a market belongs to the high-CRT treatment without *common information* and value zero otherwise.

Table A5. Mean absolute deviation comparison between the baseline and the Loan treatment.

Dependent Variable	Sample (Market / Transactions)			
MAD	Markets 14, 15 & 17 All transactions (1)	Markets 14, 15 & 17 Last 3 transactions (2)	All markets All transactions (3)	All markets Last 3 transactions (4)
Constant	-746.269***	-973.936***	80.013***	94.757***
	(129.215)	(125.461)	(20.110)	(19.838)
Loan Treatment Dummy[25]	110.889***	81.198***	59.461***	33.624***
	(11.785)	(11.247)	(14.954)	(12.392)
True Asset Value	-0.274**	-0.372***	-0.006	0.023
	(0.110)	(0.085)	(0.099)	(0.093)
Market Number	60.870***	78.699***	3.638***	3.366***
	(8.223)	(7.377)	(1.181)	(1.023)
Number of Observations	36	36	204	204
R^2	0.441	0.569	0.085	0.055
Prob > χ^2	0.000	0.000	0.000	0.000

[25] This dummy variable takes value one for a session of the Loan treatment and value zero otherwise.

Table A6. Mean absolute deviation comparison between the baseline and the High Stakes treatment.

Dependent Variable	Sample (Market / Transactions)			
MAD	Markets 14, 15 & 17 All transactions (1)	Markets 14, 15 & 17 Last 3 transactions (2)	All markets All transactions (3)	All markets Last 3 transactions (4)
Constant	-936.252*** (83.400)	-1,152.629*** (58.456)	58.221*** (14.139)	75.409*** (13.882)
High Stakes Treatment Dummy[26]	5.744 (9.870)	6.445 (5.917)	8.606 (7.776)	5.128 (6.191)
True Asset Value	-0.235*** (0.075)	-0.304*** (0.049)	0.140*** (0.052)	0.141*** (0.047)
Market Number	72.587*** (6.095)	89.199*** (3.979)	1.899*** (0.585)	2.128*** (0.280)
Number of Observations	45	45	255	255
R^2	0.626	0.849	0.105	0.107
Prob > χ^2	0.000	0.000	0.000	0.000

[26] This dummy variable takes value one for a session of the High Stakes treatment and value zero otherwise.

Table A7. Mean absolute deviation comparison between the baseline, the Loan treatment, the High Stakes treatment and high-CRT sessions with *common information*.

Dependent Variable	Sample (Market / Transactions)			
MAD	Markets 14, 15 & 17 All transactions (1)	Markets 14, 15 & 17 Last 3 transactions (2)	All markets All transactions (3)	All markets Last 3 transactions (4)
Constant	-913.865*** (100.238)	-692.337*** (111.988)	103.280*** (15.745)	90.592*** (17.066)
Treatment Dummy "CRT Common Information"[27]	-85.238*** (15.119)	-102.235*** (16.436)	-50.296*** (11.293)	-65.659*** (14.394)
True Asset Value	-0.310*** (0.058)	-0.248*** (0.067)	0.062 (0.058)	0.055 (0.062)
Market Number	74.478*** (6.237)	57.864*** (7.242)	1.918** (0.800)	1.792* (0.943)
Number of Observations	63	63	357	357
R^2	0.589	0.450	0.079	0.101
Prob > χ^2	0.000	0.000	0.000	0.000

[27] The treatment dummy "CRT Common Information" takes value one if a market belongs to the high-CRT treatment with *common information* and value zero otherwise.

Table A8. Mean absolute deviation comparison between the baseline, the Loan treatment, the High Stakes treatment and high-CRT sessions without *common information*.

Dependent Variable	Sample (Market / Transactions)			
MAD	Markets 14, 15 & 17 All transactions (1)	Markets 14, 15 & 17 Last 3 transactions (2)	All markets All transactions (3)	All markets Last 3 transactions (4)
Constant	-1,018.337*** (82.991)	-815.187*** (92.175)	96.613*** (14.909)	82.886*** (16.579)
Treatment Dummy "CRT No Common Information"[28]	-35.917*** (12.132)	-40.430** (17.643)	-25.287*** (7.295)	-26.242** (10.459)
True Asset Value	-0.361*** (0.052)	-0.264*** (0.068)	0.059 (0.057)	0.062 (0.063)
Market Number	82.153*** (4.674)	66.151*** (5.756)	2.723*** (0.625)	2.442*** (0.819)
Number of Observations	63	63	357	357
R^2	0.607	0.425	0.057	0.054
Prob > χ^2	0.000	0.000	0.000	0.000

[28] The treatment dummy "CRT No Common Information" takes value one if a market belongs to the high-CRT treatment without *common information* and value zero otherwise.

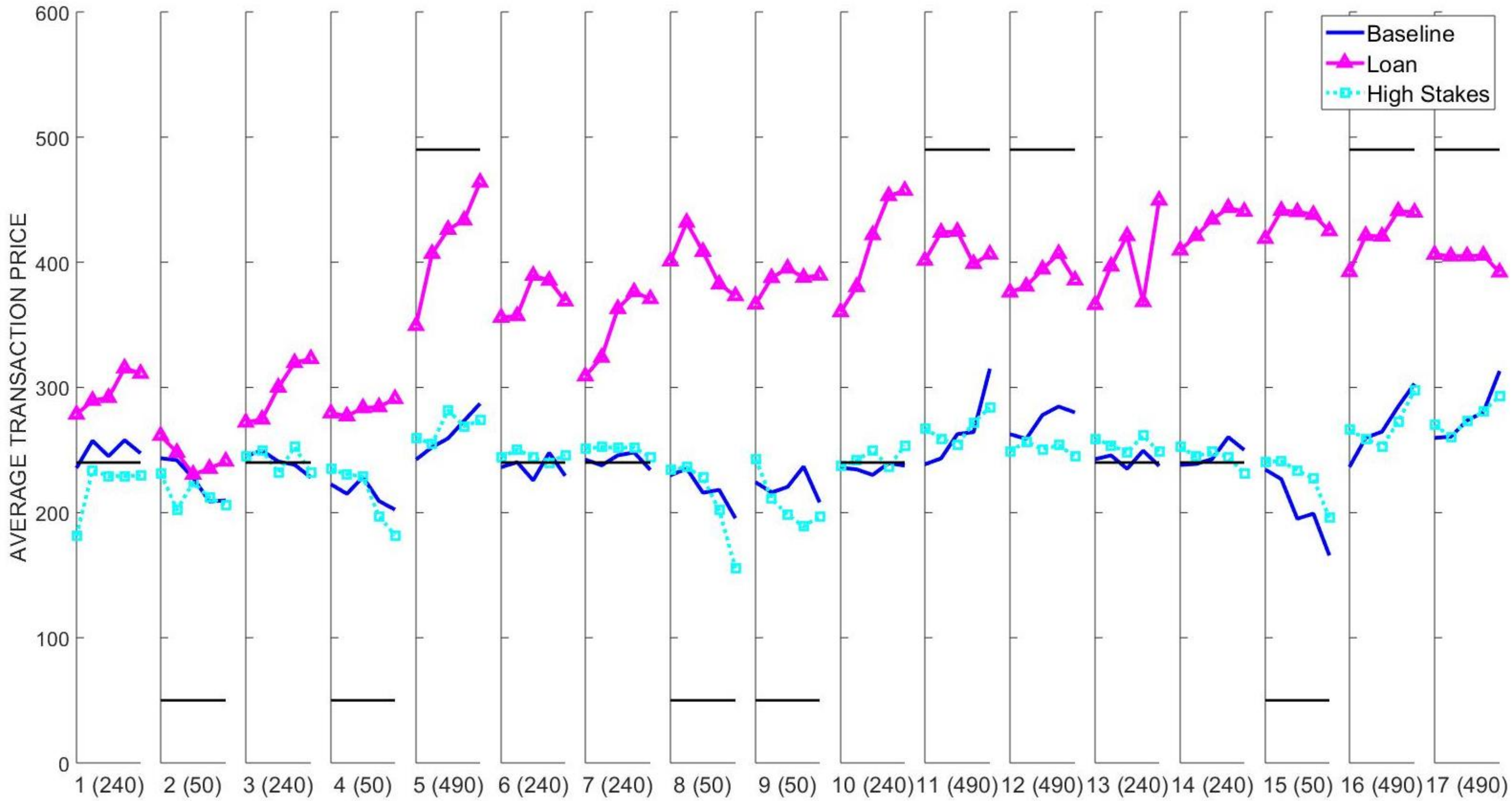

Figure A1. Average prices per minute per market for the ten baseline (solid blue lines), two Loan (solid magenta lines with triangle markers) and five High Stakes (dotted cyan lines with square markers) sessions. The true value is indicated by a solid black horizontal line. For comparison purposes the prices from the High Stakes sessions have been divided by a factor of two.