Let's chat... When communication promotes efficiency in experimental asset markets: A Review

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Working Paper

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"(…) The problem of what is the best way of utilizing knowledge initially dispersed among all the people is at least one of the main problems of economic policy—or of designing an efficient economic system."

Hayek (1945), page 520

1. Introduction

1.1. On trader communication and informational efficiency

Hayek (1945) argues in favor of markets as a mechanism to allocate scarce resources by putting forward their unique capacity to aggregate widely dispersed information. Beyond its eloquence and intuitive appeal, the Hayekian argument is difficult to test, given that we typically do not observe private information. When testing the informational efficiency of markets with field data, we cannot disentangle whether it results from the market pricing mechanism per se or other socially-relevant aspects of the exchange institution (Polanyi, 1957). Stock markets are institutions *embedded* in a social context in which market participants not only transmit information to each other via market prices but also via verbal and informal communications (e.g., Shiller, 1984; Granovetter, 1985). Sharing information actually seems to be an inherent characteristic of humans (Tamir, Zaki and Mitchell, 2015).[1] Yet, little is known about the interaction between social and market institutions.[2]

We aim to illustrate the relevance of this interaction by focusing on the emerging prominence of social platforms in financial markets. The use of communication (chat) platforms customized for the stock market has dramatically increased in recent years due to new information technologies (e.g., Pike, 2015).[3] One of the most popular chat platforms is 'Bloomberg Instant Messaging,' which created a panic by briefly shutting down on the 2016 US Election Day.[4] A prior Bloomberg two-hour crash (between 7:20 a.m. and 9:00 a.m., GMT) on the 17th of April 2015 created a similar state of anxiety.[5] European markets, which were opening at the time of the Bloomberg shutoff, exhibited

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[1] Tamir, Zaki and Mitchell (2015) show that people are inclined to share information whenever they are given the possibility to do so even when it consists of useless packets of meaningless numbers (1, 2, 3 or 4).

[2] Thus far, the study of market design has been largely isolated from the research on social motives in Economics (Smith, 2007). This is perhaps reminiscent of the tension between the "two faces of human nature": non-cooperative 'self-interest' and other-regarding 'sympathy' (see Smith, 1998, 2007) which were separately studied in the two major writings of Adam Smith (1759, 1776).

[3] https://www.quora.com/What-stock-chat-rooms-are-the-best

[4] http://www.businessinsider.fr/uk/bloombergs-chat-function-stops-working-on-election-day-2016-11/

[5] https://www.ft.com/content/2fc47e84-e4e3-11e4-bb4b-00144feab7de; http://in.reuters.com/article/markets-bonds- britain-idINKBN0N81EP20150417

a spike in volatility, and the index of Europe's top 300 companies (*FTSEurofirst 300 Index*) was down 1.6% by the end of the morning.

Perhaps surprisingly, this price movement was not attributed to the shutdown of charts and data feeds but to the shutdown of the chat platform. This ability to communicate with other market participants is valued as an essential part of the Bloomberg terminal services (e.g., Pike, 2015).[6] Consider the following quote by a Hong Kong-based banker interviewed by the *New York Times*:[7]

"*What I miss is the instant Bloomberg chats, which I rate higher than trading or data feeds. The fact is, Bloomberg connects 100 percent of the Street, and all that human intelligence is what makes markets hum*."

Bloomberg's competitors have recently responded to the growing demand for stock market chat rooms by developing specific platforms (e.g., *Symphony*) that allow traders to subscribe to a chat service without paying for any additional (market-based) services.

It is unclear, however, why trader communication is so highly valued by market participants. One possibility is that communication facilitates the completion of transactions by allowing traders to share information about market valuations.[8] This feature of "chatting" may be especially relevant when the information to be shared is highly dispersed among market participants, which makes the aggregation of traders' private information very challenging (Corgnet, DeSantis and Porter, 2019). Unfortunately, Bloomberg chats are deemed to be sensitive proprietary data and thus have not been used for research purposes. As such, a recent study by Chen et al. (2014) used a popular stock-related billboard website (*Seeking Alpha*) to assess whether the reports posted on the platform have any predictive power on the stock market. Using textual analysis to compute the frequency of negative words, the authors show that the tone of *Seeking Alpha* reports was a successful predictor of future stock returns and earnings.[9] The positive results of Chen et al. (2014) must, however, be

[6] https://www.ft.com/content/39113276-a5d4-11e6-8898-79a99e2a4de6
[7] http://www.businessinsider.fr/us/the-bloomberg-feature-every-trader-felt-lost-without-2015-4/
https://www.nytimes.com/2015/04/18/business/dealbook/bloomberg-terminals-outage.html?_r=1
[8] Alternatively, chat platforms might help traders complete deals.
[9] Another example demonstrating the impact of chat rooms on stock prices is provided by the following New York Times article:
https://www.nytimes.com/2000/09/21/business/sec-says-teenager-had-after-school-hobby-online-stock-fraud.html, which describes a teenager's strategy of buying a stock and then posting optimistic messages in several online chat rooms.

contrasted with a wealth of inconclusive evidence regarding the predictive power of online message boards on the stock market (e.g., Tumarkin and Whitelaw, 2001; Antweiler and Frank, 2004; Das and Chen, 2007). The mixed results from these archival studies are partly explained by differences in the structure of the communication platforms under study (see Chen et al. 2014). The analysis of Chen et al. (2014) relied on a highly structured communication platform with an active editorial board, whereas the three previously referenced studies focused on more unstructured open message boards. More importantly, the aforementioned studies rely on archival data, which makes it difficult to assess the amount of information communicated through these online platforms. In the hypothetical case in which such an assessment is possible, it would still be important to identify the motives of individuals who release their private information to the online community. Chen et al. (2014) offer several possible explanations including both monetary motives, such as building a reputation in order to redirect social media users to paid services, as well as non-monetary motives, such as prestige and recognition. As is argued by Chen et al. (2014, p. 1371), studying "the relative importance of some of the aforementioned mechanisms is difficult to assess empirically."

To avoid the issues confronting archival studies, we conducted asset market experiments. These markets enable us to study the causal effect of trader communication on the efficiency of markets and to identify traders' motives to share their private information. The experimental methodology offers control of both the asset value and the distribution of private information, which allows us to assess the aggregation of private information (see Hayek, 1945; Fama, 1970).[10] In addition, the use of experimental markets allows us to separate the market as a pricing mechanism from its social context thus isolating the unique effect of trader communication on market efficiency (see Smith, 1976; Bossaerts, 2009; Frydman et al. 2014; Noussair and Tucker, 2014).

The closest paper to ours is the recent experimental work of Halim, Riyanto and Roy (2018), which assesses the effect of social networks on traders' incentives to acquire information. This acquisition, in turn, impacts the aggregation of information in markets. They envision a social setup in which networks are composed of traders who reveal their information to each other. They mention mutual

According to the article, his strategy was successful, though he was ultimately sued by the S.E.C. and forced to repay his earnings.

[10] As is noted by Fama (1991) himself, the effectiveness of using actual market data to investigate informational efficiency is limited.

trust and friendship as key characteristics of such networks. In that context, they highlight an interesting free-riding effect of social networks according to which well-connected traders might wait for other traders to acquire costly information as they know it will be costlessly and honestly shared with them. It thus follows that social networks, despite promoting the sharing of information, might negatively affect the ability of prices to reflect all available information. We focus our efforts on a different scenario in which the transmission of information between traders is voluntary and not necessarily truthful. We are thus interested in the strategic transmission of private information among traders in the absence of social networks and costly acquisition of information. In doing so, we take up where Halim, Riyanto and Roy (2018) left off:

"Finally, we focused on a network of trusted friends who honestly reveal their private information. It would be interesting to study strategic information transmission, including the possibility of lying and manipulation of information revealed to neighbors."

The only other experimental papers of which we are aware that study the effect of trader communication on market outcomes utilize a design in which the markets are prone to bubbles and crashes (Smith, Suchanek and Williams, 1988). The objective of these studies (Oechssler, Schmidt and Schnedler, 2011; Hargreaves-Heap and Zizzo, 2011) was to assess whether allowing traders to communicate could spur 'animal spirits' leading to amplified bubbles and subsequent crashes. Contrary to their predictions, they did not find that traders' chats fostered bubbles. That said, these studies were not focused on the study of information aggregation in markets or the design of institutions more generally. Traders in Hargreaves-Heap and Zizzo (2011) were not given private information thereby precluding the study of information aggregation. The design of Oechssler, Schmidt and Schnedler (2011) includes a limited amount of private information as only one out of the ten market participants was given, with probability 50%, a private signal about the value of one of the five assets traded in the experiment. Thus, their work sharply differs from ours as it neither studies the aggregation of dispersed information nor the design of communication platforms.

1.2. Overview of our study

To test the aggregation of private information, we use the seminal design of Plott and Sunder (1988), in which 12 traders participate in a sequence of 17 market periods. In each market period, an experimental asset that can only take one of three possible values, 50, 240 or 490, with varying probabilities is traded. At the beginning of each market period, each trader is informed of a 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. In addition to the baseline (*No Chat*), we conducted two main communication treatments in which we allowed market participants to send fixed messages to each other. In both communication treatments, we allowed participants to send as many messages as they wanted during a one-minute interval prior to each market period. The set of fixed messages was restricted to the possible private signals: "Not 50", "Not 240" and "Not 490".

We develop testable hypotheses putting forth the role of social motives in communication (Shiller, 1984) that we formalize by relying on recent models in the deception literature (see Abeler, Nosenzo and Raymond, 2018 and Gneezy, Kajackaite and Sobel, 2018). These models account for pervasive truth-telling in standard deception games (Fischbacher and Föllmi-Heusi 2008; Shalvi, Dana, Handgraaf and De Dreu, 2011), despite a monetary cost to do so, by positing that people suffer from direct lying costs as well as reputational costs from being seen as dishonest. Incorporating these two ingredients in our model, we show that traders might share their private information when chatting is allowed leading market prices to more closely reflect the true asset value. To assess the relative importance of each of the motives for truth-telling, we designed two communication treatments, which we compare to the *No Chat* baseline.

In the first communication treatment (*Chat*), we displayed a "reputation" score for each participant replicating standard features of traders' chat rooms (e.g., *StockTwits* and *Symphony*). This score was calculated as the proportion of other traders who were not actively blocking the participant's messages. In our second chat treatment (*Chat-no reputation*), we isolate the direct effect of lying costs on truth-telling from the effect of reputational concerns by disabling "reputation" scores.

In the *Chat* treatment, informational efficiency was substantially higher than in the *No Chat* baseline. Average prices in the *Chat* markets deviated from the true asset value by only 19%, whereas this deviation was 57% for the *No Chat* markets. *Chat* was effective in conveying private information to market prices because each trader sent at least one message per market period in an overwhelming majority (91%) of the cases, and their messages were *informative* (e.g., messages "Not 50" or "Not 490" when the true asset value is 240) in more than 80% of the cases. Truth-telling was thus pervasive even though market participants were (individually) harmed by releasing their private information as it left them at an informational disadvantage. Because these markets are zero-sum games, conveying one's private information to other traders would lead to lower earnings. Despite this cost, market participants were likely to share their private information and, more generally, to communicate informative messages. This is in line with our model in which truth-telling is spurred by both direct lying costs and reputational concerns for honesty. A driving force behind truth-telling in the *Chat* treatment relates to traders actively blocking messages from other traders who submitted *misleading* messages that were not consistent with the true asset value (e.g., sending the message "Not 240" when the true asset value is 240). It follows that a traders' ability to manipulate prices to their advantage through chat messages was limited, and, consequently, the communication platform positively impacted the informational efficiency of the markets.

The *Chat-no reputation* treatment allowed us to quantify the key role of reputational concerns by showing that informational efficiency is substantially reduced when "reputation" scores are disabled. In particular, the proportion of misleading messages per trader almost doubled in the *Chat-no reputation* treatment (21.9%) compared to the *Chat* treatment (12.3%). This was likely because misleading messages could not be sanctioned by a lower "reputation" score. As a consequence, traders who released a larger proportion of misleading messages in the *Chat-no reputation* treatment achieved higher earnings, whereas the opposite was observed in the *Chat* treatment. The *Chat-no reputation* treatment also showed, in line with our model, that people who earned a high score on a validated honesty scale (see Ashton, Lee and de Vries, 2014) were more inclined to release informative messages in the communication platform. This was the case even after controlling for standard measures of prosociality (see Bartling et al. 2009) and cognitive skills (see Bruguier, Quartz and Bossaerts, 2010; Noussair, Tucker and Xu, 2014; Hefti, Heinke and Schneider, 2016; Corgnet, DeSantis and Porter, 2018). Importantly, chat improved the informational efficiency of markets even in the absence of reputational concerns because price deviations from the true asset value were significantly lower in the *Chat-no reputation* treatment compared to *No Chat*.

Finally, we demonstrate the robustness of our results in a series of additional treatments. In particular, we found that our results continue to hold when, for example, communication and trading occurred at the same time as well as when traders were allowed to send free-form instead of fixed messages. In both treatments, informational efficiency was higher than under *No Chat* thus confirming the positive effect of chat on the informational efficiency of markets. We also showed our results to be robust to different types of private signals and to alternative distributions of private information. Lastly, we found that chat could also promote allocative efficiency in a setup in which we introduced mutual gains from exchange.

Our findings highlight how one's preference to be honest, as well as one's preference to be seen as honest, can help markets achieve informational and allocative efficiency. These results relate to the concept of *embeddedness* (Granovetter, 1985) according to which economic institutions are 'constrained by social relations'. In our case, the social context, rather than acting as a constraint, appears to facilitate the effectiveness of the market institution. Ours is the first study to demonstrate the causal effect of communication on promoting the informational and allocative efficiency of markets.

2. Experimental Design

2.1. Main treatments

Our study uses the design of Plott and Sunder (1988), which introduces an experimental asset that can take the value of 50, 240 or 490 francs (each franc was worth $0.001) with probability 35%, 45% or 20%, respectively.[11] The asset was traded in a computerized continuous double auction.

Each of the twelve traders in the market was privately informed of a value the asset <u>could not</u> take. As 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"), the aggregate information available to traders in the market was complete. Traders were endowed with 1,200 francs in cash and four shares of the asset. Each session consisted of 17 five-minute market periods with independent value draws.[12]

In addition to the *No Chat* sessions, which used the above specifications, we conducted two communication treatments in which we allowed market participants to send fixed messages to all traders or a subset of traders at their discretion. The set of messages included each possible private signal (i.e., "Not 50", "Not 240" and "Not 490").[13]

[11] We used the parameters of Market 9 ('Series C') from Plott and Sunder (1988).
[12] We used the values from Market 9 of Plott and Sunder (1988) for each session.
[13] For ease of exposition, we refer to the message "The dividend is Not 50/240/490" as "Not 50/240/490".

In our first communication treatment (*Chat*), participants were allowed to send as many messages as they wanted for one minute prior to each market period. Market participants were identified by an ID letter (from A to L) which was randomly assigned each market period to avoid any reputation effects across periods (see Figure 1). All market transactions were anonymous and not linked to the Chat ID. On the right side of the chat interface, participants saw a Chat History panel that displayed the content of previously received messages along with the Chat IDs of the sender and the receiver(s). A pie chart summarized the history of chats sent by other participants.

Our chat platform allowed participants to filter messages sent by another trader(s) by clicking on a green disk located to the left of the participant's Chat ID. By doing so, all previous and future messages of the filtered trader(s) would no longer appear in the Chat History panel (or the pie chart) and a red cross would appear to the left of the filtered participant's ID. At any moment, a trader could unfilter another trader's messages by clicking on the red cross (see Figure 1). In addition, the chat interface displays a "reputation" score for each participant. This score is calculated as the proportion of other traders who are not actively filtering the participant's messages. The score equals 100% if no other traders are filtering a trader's messages. It equals 91% if only one other trader is currently filtering that participant's messages (see the participant with Chat ID "F" in Figure 1).

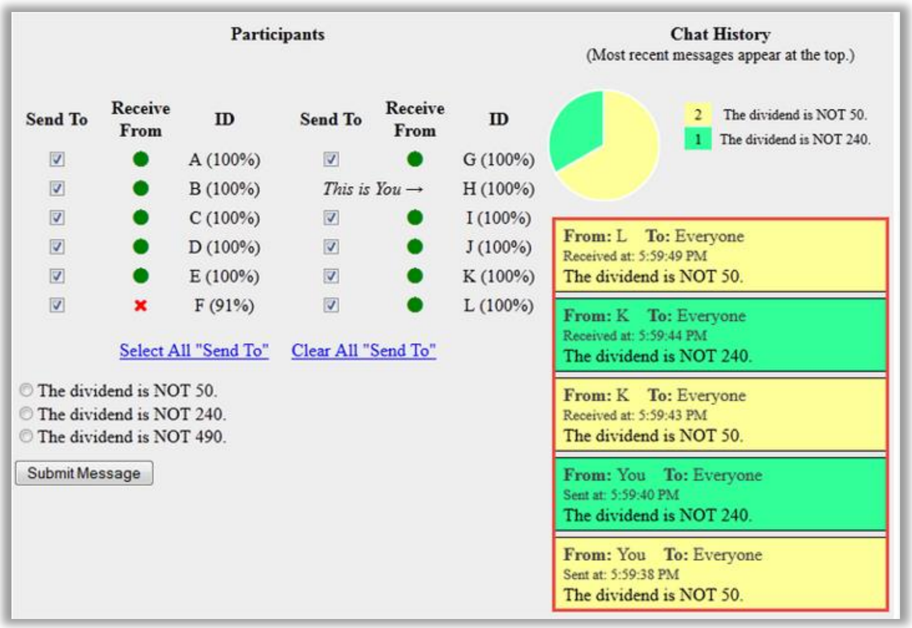

Figure 1. Chat interface.

To isolate the effect of the “reputation” score on the effectiveness of chat in promoting the aggregation of dispersed information, we consider an additional treatment (*Chat-no reputation*) in which participants cannot filter each other’s messages so that no “reputation” score is available on the screen. The chat interface (see Figure 1) was slightly modified for this treatment by removing the “Receive From” columns (along with the green disks/red crosses) as well as the reputation scores.

We summarize the treatments in Table 1. The full set of instructions for all treatments is provided in the Internet Appendix Section IV.

Table 1. Summary of the Experimental Design

	Treatment	*Chat platform*	*Number of Markets* (Sessions)	*Endowment in Francs* (Assets)	*Asset Values in Francs* (Probabilities)
Main treatments	*No Chat*	None	17 (10)	1,200 (4)	50, 240, 490 (0.35,0.45,0.20)
	Chat	One-minute fixed chat before each market	17 (8)		
	Chat-no reputation	One-minute fixed chat before each market No reputation score	17 (8)		
Robustness treatments	*Chat-during*	Fixed chat available during each market	17 (8)	1,200 (4)	50, 240, 490 (0.35,0.45,0.20)
	Free-form Chat	Free-form chat available during each market			
	No Chat-probabilistic	None	10 (5)	1,200 (4)	50, 240, 490 (0.35,0.45,0.20)
	Chat-probabilistic	One-minute fixed chat before each market			
	No Chat-insider	None	17 (5)	1,200 (4)	50, 240, 490 (0.35,0.45,0.20)
	Chat-insider	One-minute fixed chat before each market			
	Private Value-No Chat	None	10 (5)	1,500 (3)	100, 240, 300 (1/3,1/3,1/3) & 290, 190, 160 (1/3,1/3,1/3)
	Private Value-Chat-during	Fixed chat available during each market			

2.2. Robustness treatments

For the sake of robustness and because markets and chat inevitably occur concurrently in actual stock exchanges, we conducted the *Chat-during* treatment in which market participants could communicate for the entire duration of each market period (but not prior to a market period).

We also conducted a chat treatment in which participants could compose and send text messages for the duration of a market period (*Free-form Chat*). The goal of this treatment was to consider a communication environment that more closely resembles the 'Bloomberg Instant Messaging' platform. The free-form chat interface is similar to that of the fixed message treatments. One slight difference is that the pie chart (see top right corner of Figure 1) is not displayed because, unlike fixed messages, free-form messages could not easily be categorized into predefined groups (e.g., "Not 50", "Not 240" and "Not 490"). Otherwise, the design of *Free-form Chat* was identical to that of the main treatments (see Table 1).

To better understand the impact of the structure of private information on both market efficiency as well as the participants' propensity to truthfully reveal this information, we conducted the *Chat-probabilistic* and *Chat-insider* treatments (along with the corresponding baseline treatments without chat). In *Chat-probabilistic* traders' private signals were accurate 80% of the time and inaccurate 20% of the time. In *Chat-insider* two of the 12 traders were fully informed of the true asset value, while the other 10 traders did not receive a private signal. In these sessions, we used the same trading rules and number of traders as in the main treatments. However, we shortened the length of the experiment by conducting 10 four-minute market periods instead of 17 five-minute market periods.[14]

The *Chat*, *Chat-no reputation*, *Chat-during*, *Free-form Chat*, *Chat-probabilistic* and *Chat-insider* treatments allow us to study the informational efficiency of markets by assessing the extent to which prices incorporate traders' private information. However, these treatments do not allow traders to mutually gain from exchange. To address this, we designed two additional treatments following the work of Plott and Sunder (1988) (see Treatment 'Series A'). In this design there exist three equally likely states of the world denoted X, Y and Z with the asset value dependent upon the realized state (similar to our previous treatments). However, in each state of the world, the asset value differed across two groups of traders. In state X (Y) [Z], the asset value was equal to 100 (240) [300] francs

[14] This allowed us to shorten the length of the experiment while still providing traders with the opportunity to learn.

for one-half of the traders and 290 (190) [160] for the other half. In this setting, gains from exchange are realized whenever traders with a lower value for the asset sell to those traders with a higher value. As in the *Chat-probabilistic* and *Chat-insider* treatments, we used the same trading rules and number of traders as in the main treatments. However, we again shortened the length of the experiment by conducting 10 four-minute market periods instead of 17 five-minute market periods. At the beginning of each period, participants were endowed with 1,500 francs and three shares of the asset.[15] We conducted a baseline (*Private Value-No Chat*) and one chat treatment (*Private Value-Chat-during*). The chat platform is similar to *Chat-during* in which traders could send fixed messages at any point during the market period. Because different groups of traders had different private values in a given state of the world, we designed fixed messages so that traders could communicate with respect to the state of the world rather than asset value. Thus, we were able to keep the number of fixed messages to three (i.e., "Not X", "Not Y" and "Not Z") as in the main *Chat* treatments.

2.3. Procedures

We conducted 10 baseline (*No Chat*) sessions along with 8 sessions each for *Chat and Chat-no reputation*.[16] The average earnings of each participant in these main treatments were $49 including a $7 show-up payment. The average earnings of each participant for the robustness treatments were $44 including a $7 show-up payment.[17,18] To ensure participants were substantially incentivized, we paid, on average, approximately 30% more than a typical experiment of similar length at the lab where the study was conducted. The 17-market period sessions lasted approximately 2.5 hours, while the 10-market period sessions lasted approximately 1.5 hours.

We recruited a total of 864 individuals from a large participant pool at a major Western US University. Before the trading phase of each session started, participants completed a training

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[15] We had to slightly adjust traders' cash and shares endowment compared to previous treatments to keep average trader earnings per hour constant across treatments.

[16] Because of the large number of treatments in Table 1, we conducted fewer sessions than in our *No Chat* baseline. The data for the *No Chat* sessions are also used as baseline sessions in Corgnet, DeSantis and Porter (2018).

[17] These are market earnings that exclude the social preference task payment randomly received by two participants in each session.

[18] The probabilistic signals, insider and private values treatments are primarily intended to serve as additional robustness checks for our main analyses. As such, we conducted five sessions per treatment instead of eight as with the other chat treatments. In addition, we conducted sessions with 10 instead of 17 markets for the probabilistic and private values sessions to reduce the costs of the experiments.

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 period.[19] During the training, participants had to predict the outcome of the spinning wheel over 10 trials (see Internet Appendix Section IV). Each correct prediction was rewarded 25 cents, and each incorrect answer incurred a 10-cent penalty as in the original design of Plott and Sunder (1988). After the instructions, participants completed a comprehension quiz on the mechanics of the market (see Internet Appendix Section IV) and participated in a non-incentivized practice market period. Note that participants could not begin the practice period until they correctly answered all quiz questions.

2.4. End-of-experiment survey

After the final market trading period, participants responded to questionnaires regarding various psychological traits and cognitive skills as well as demographic characteristics. We elicited participants' cognitive reflection (Frederick, 2005) and theory of mind skills (see Baron-Cohen et al. 1997) using the Cognitive Reflection Test, (CRT, henceforth) and the eye gaze test (TOM, henceforth). These skills have been identified as predictors of traders' earnings in experimental markets (see Bruguier, Quartz and Bossaerts, 2010; Noussair, Tucker and Xu, 2014; Hefti, Heinke and Schneider, 2016; Bossaerts, Suzuki and O'Doherty, 2018; Corgnet, DeSantis and Porter, 2018). We also collected individual data on an incentivized social preference task (Bartling et al. 2009).[20] The duration of the survey was 25 minutes. These tasks were computerized and, as is common practice in the literature, the CRT and TOM tests were not incentivized. In addition to the social preference task earnings, participants earned a $3 payment for completing the survey (see Internet Appendix Section II).[21] In the *Chat-no reputation* treatment, we also elicited the honesty-personality dimension using the HEXACO scale (see Ashton, Lee and de Vries, 2014).

We next derive hypotheses regarding the effect of trader communication on the informational efficiency of markets.

[19] This training exercise was not conducted for the private values sessions as each state of the world was equally likely.
[20] The social preference task was not utilized for the *No Chat* baseline and the first four sessions (each) of the *Chat* treatment as we had previously collected such information for each of these participants in an independent survey conducted at the lab where the study was implemented (see Corgnet, DeSantis and Porter, 2018 for more details on this independent survey). The independent survey was conducted approximately one month before the *No Chat* sessions were run.
[21] Participants received a $5 payment for completing the survey in the *Chat-no reputation*, *No Chat-probabilistic*, *Chat-probabilistic* and *Chat-insider* treatments.

3. Hypotheses

To derive our hypotheses, we consider a *chat & trading* game (see Appendix C for details of the model). As in our *Chat* treatment, we assume chat and trading occur sequentially in two separate stages. The model environment closely follows our experimental design

In the first stage, given their private signal, participants can send a message to all other participants regarding one of the three values the asset cannot take. The asset is then traded in the second stage. For our analysis, we focus on *truthful communication equilibria* in which all traders send truthful messages, and messages are believed to be truthful. We disregard the study of equilibria in which no information is transmitted in the chat platform, as would be the case if traders did not send any messages in equilibrium or if they randomized between messages.

We start by assuming all traders are *asocial*, thus only maximizing their own material payoff. In the case in which these asocial traders are rational, we show that sending messages cannot affect asset prices. This is because all private information will necessarily be transmitted to prices in the second stage (see Appendix C.1.1). When all traders are rational, informational efficiency is thus achieved in the absence of communication, which trivializes the impact of the chat platform.[22] In the case of non-rational, asocial traders, market prices may not reflect true asset value so that messages might convey valuable information to other traders. Given the emerging empirical support for cursed trading in which individuals fail to recognize information in prices (e.g., Corgnet, DeSantis and Porter, 2015; Magnani and Oprea, 2016), we consider the case in which traders' bounded rationality arises from their failure to infer other traders' private information from asset prices (Eyster, Rabin and Vayanos, 2018). Non-rational traders are thus modeled as *cursed* traders. When all traders are cursed, a truthful communication equilibrium does not exist because traders would have an incentive to deviate to obtain an informational advantage. This holds because, unlike the case of rational traders, the market price no longer conveys the true asset value to traders. It follows that traders who deviate from the truthful communication equilibrium could effectively manipulate other traders' beliefs regarding the true asset value by sending a message that differs from their private signal. For example, a trader endowed with the signal "Not 490" will have an

[22] The case of rational traders is one in which the no-trade theorem applies so that traders would be indifferent between trading at a price which is equal to the true asset value or not trading (Milgrom and Stokey, 1982).

incentive to release a different signal (e.g., "Not 50") in order to raise other traders' beliefs about the true asset value. This holds because, in a truthful communication equilibrium, any message sent during the first stage is believed to be true.

In summary, in the presence of asocial traders, communication is either irrelevant (rational traders) or not truthful (cursed traders). We make the following hypothesis regarding the effect of communication on the informational efficiency of markets populated by asocial traders.

Hypothesis (Asocial Traders) *In the presence of asocial traders, the ability to communicate will not improve the informational efficiency of markets*.

We now consider the case of *social* traders who might have a natural inclination to share truthful messages with others.[23] The large and growing deception literature has convincingly shown that lying is costly to people.[24] In line with this research, we first model social traders as those suffering from a direct cost of lying (see Appendix C.1.2).

In the case in which the market is populated with social cursed traders, there exist equilibria in which communication improves the informational efficiency of markets. This is the case because a *truthful communication equilibrium* exists whenever traders suffer from direct lying costs. This follows from the fact that it is costly for social traders to deviate from such an equilibrium as it involves lying. We thus derive the following hypothesis for the case of social traders.

Hypothesis (Social Traders) *In the presence of social cursed traders, communication will lead to the release of truthful messages as long as direct lying costs are large enough, thereby promoting the informational efficiency of markets*.

The recent works of Abeler, Nosenzo and Raymond (2018) and Gneezy, Kajackaite and Sobel (2018) have shown that people's inclination to tell the truth is not only driven by the existence of a direct cost for lying (i.e., preference for being honest) but also by their desire to be seen as honest.

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[23] We do not use the term prosocial which is more closely related to altruistic motives. The term 'social' we employ is more closely related to the broader term of homo socialis (see e.g., Gintis and Helbing, 2015) which encompasses moral, social and other-regarding motives.

[24] Some of the papers in this literature include Gneezy (2005); Dreber and Johannesson (2008); Fischbacher and Föllmi-Heusi (2008); Mazar, Amir and Ariely (2008); Lundquist, Ellingsen, Gribbe and Johannesson (2009); Sutter (2009); Shalvi, Dana, Handgraaf and De Dreu (2011); Erat and Gneezy (2012); Abeler, Becker and Falk (2014); Cohn, Fehr and Maréchal (2014); Abeler, Nosenzo and Raymond (2018) and Gneezy, Kajackaite and Sobel (2018).

This implies that any mechanism that publicizes traders' reputation for being honest will magnify the costs of lying and thus further promote truth-telling. In our *Chat* treatment, unlike the *Chat-no reputation* treatment, we endow traders with such a mechanism as they can publicly observe a "reputation" score for each trader which decreases as other traders filter that trader's messages. To assess the impact of this mechanism in our model, we extend our analysis to the case in which traders can filter another trader's message thereby lowering that trader's "reputation" score. This filtering stage is added to our model immediately after traders have decided which message to send and before trading occurs (see Appendix C.2). The filtering stage enlarges the possible set of *truthful communication equilibria* thus generally promoting truth-telling and informational efficiency. This is the case because, in the presence of a filtering stage, *truthful communication equilibria* can exist even when direct lying costs are absent. These equilibria occur whenever traders' filtering strategies reveal whether a trader is a liar. For example, we denote *reputation-truthful equilibria* as those *truthful communication equilibria* in which traders decide to filter a trader's message if it is not consistent with their own message. In that case, liars would certainly be identified as their messages would be filtered by all other traders leading to the lowest possible "reputation" score. As long as being identified as a liar is sufficiently costly, a social trader will not deviate from telling the truth in equilibrium even if their direct cost of lying is zero.

We summarize the impact of using "reputation" scores in the chat platform in the following hypothesis.

Hypothesis (Reputation) *In the presence of social cursed traders, the existence of a reputation score will facilitate the release of truthful messages compared to a case in which such a score is not available, thereby promoting the informational efficiency of markets*.

Our hypotheses put forth the crucial role of communication across traders to achieve informational efficiency. Even more subtly, it provides guidance for designing communication institutions that will leverage the social motives of traders to release informative messages and thus facilitate information aggregation in markets.

4. Results

4.1. On the informational efficiency of chatting

Figure 2 displays the average price per minute per market period across all sessions for our main treatments: *No Chat*, *Chat* and *Chat-no reputation* (see Internet Appendix Section I for graphs of transaction prices per market period for each session).

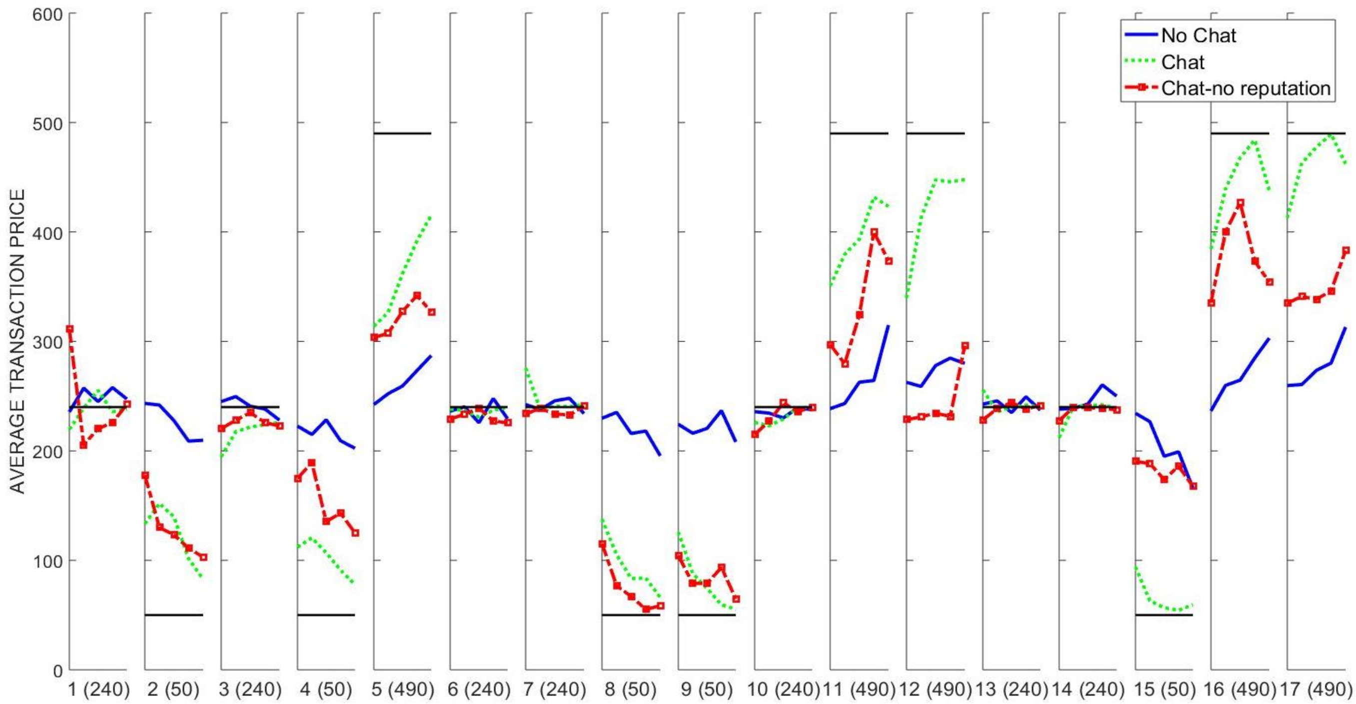

Figure 2. Average price per minute over the 10 *No Chat* sessions (solid blue curve), the eight *Chat* sessions (dotted green curve) and the eight *Chat-no reputation* sessions (dash-dot red curve with square markers) for each of the 17 market periods. The true asset value is denoted at the bottom of each subfigure and displayed as a solid (black) horizontal line.

We observe that average prices are significantly closer to the true asset value for the chat treatments compared to *No Chat*. Following the work of Plott and Sunder (1988) and Corgnet, DeSantis and Porter (2015), we focus our statistical analyses on the last occurrence of each of the possible asset values: 50, 240 and 490 (i.e., markets 15, 14 and 17, respectively). To assess informational efficiency, we report for each session the mean absolute deviation between the price and the true asset value calculated as:

$$\underset{i}{\text{average}}\left|p_i - True\ value\right| \quad (1)$$

where i represents a transaction and p_i corresponds to the transaction price. Thus, the mean absolute price deviation (MAD) is computed as the average over all transactions in markets 14, 15 and 17 for each session. In line with Figure 2, we find that the MAD is significantly lower in the *Chat* treatment (p-value < 0.001, Wilcoxon Rank Sum test, WRS henceforth) compared to *No Chat* (see Table IAVI in Internet Appendix Section III for session values). The *Chat-no reputation* treatment also exhibits a significantly lower MAD than the *No Chat* baseline (p-value = 0.006, WRS). These results are in line with our *Social Traders* hypothesis, which suggests that the presence of chat, even in the absence of a reputation mechanism, would increase the informational efficiency of the market. In addition, we support our *Reputation* hypothesis by showing that informational efficiency (as measured by equation (1)) is lower in the absence of a reputation mechanism (*Chat-no reputation* treatment) than in its presence (*Chat* treatment) (p-value = 0.027, WRS). The previous tests are based on independent observations as one average MAD value is calculated for each session. As an alternative analysis, we consider linear panel regressions that use the MAD of a given market period for a given session as the dependent variable. A dummy variable, *Chat & Chat-no reputation* Dummy, that takes the value one if the observation corresponds to a chat treatment and zero otherwise, is included in columns (1) and (2) of Table 2. Dummy variables for each individual chat treatment (*Chat* Dummy and *Chat-no reputation* Dummy) are included as independent variables in columns (3) and (4). Controls for the market period number, *Market Number*, and true asset value, *True Value*, are also included. We use cluster-robust standard errors at the session level (see Table 2).

In the bottom panel of Table 2 (χ^2 Coefficient Tests), we also compare MAD values across chat treatments by testing the equality of coefficients between the two chat treatment dummy variables. We confirm our previous findings, that were based on non-parametric tests, as (i) all chat dummy variables are negative and significant and (ii) the magnitude of the *Chat-no reputation* Dummy variable is significantly smaller than that of the *Chat* Dummy variable.

Table 2. Treatment Comparisons for MAD Values per Market Period[25]

This table reports the results from linear panel regressions with random effects and cluster-robust standard errors at the session level (reported in parentheses). The number of observations corresponds to the number of sessions (26) multiplied by the appropriate number of market periods (three in specifications (1) and (3) and 17 in specifications (2) and (4)).

Sample	Last Three Markets (1)	All Markets (2)	Last Three Markets (3)	All Markets (4)
Intercept	109.177***	91.755***	109.177***	91.755***
	(8.472)	(10.588)	(8.772)	(10.600)
Treatment Dummy Variables				
Chat & Chat-no reputation Dummy	-74.096***	-57.634***	-	-
	(12.813)	(9.404)		
Chat Dummy	-	-	-109.721***	-77.428***
			(5.802)	(8.641)
Chat-no reputation Dummy	-	-	-38.845**	-37.841***
			(16.452)	(12.413)
Market characteristics				
Market Number	-	-0.277	-	-0.277
		(0.654)		(0.655)
True Value	0.104***	0.162***	0.104***	0.162***
	(0.029)	(0.029)	(0.029)	(0.029)
Treatment differences				
χ^2 Coefficient Tests				
Chat vs. *Chat-no reputation*	-	-	<0.001	0.006
Observations	n = 78	n = 442	n = 78	n = 442
Prob > χ^2	0.000	0.000	0.000	0.000
R^2	0.218	0.204	0.320	0.237

*p-value<0.10, **p-value<0.05 and ***p-value<0.01

In the mechanisms underlying our hypotheses, the positive effect of communication on informational efficiency relies upon the sending of informative messages by *social* traders. We study this mechanism next.

[25] Following Cameron and Miller (2011), we also estimated standard errors using the wild bootstrap procedure. The use of this procedure led to p-values that are similar to the ones reported in the results section.

4.2. On the social motives of truth-telling

For the communication platform to have any effect on efficiency, traders must send messages. This was the case in the two main chat treatments. On average, a trader sent approximately 38 messages throughout the 17-market period experiment (see the Total Number Messages value in column (1) of Table 3). Participants sent approximately 25% more messages in the *Chat-no reputation* treatment than in the *Chat* treatment though this difference is not statistically significant (see column (1) in Table 3).

Although sending messages is a necessary condition for communication to improve informational efficiency, it is crucial to assess the extent to which these messages are informative. Table 3 also reports the number of messages that are consistent with the true asset value (informative message). These messages can either state one's own private signal (exact message) or state the complementary signal required to learn the true asset value. A message (e.g., "Not 50") that differs from one's own private information (e.g., Not "490") can still be informative if it allows other traders to uncover the true asset value (e.g., "240"). By contrast, we refer to misleading messages as those that differ from the true asset value. A large proportion of traders' messages were informative (87.7% in the *Chat* treatment and 78.1% in the *Chat-no reputation* treatment), which mechanically implies that only a small fraction of messages was misleading (see column (5) in Table 3).

The average number of exact messages (misleading messages) sent by a trader throughout the entire experiment is significantly higher (lower) in the *Chat* treatment compared to the *Chat-no reputation* treatment as long as we control for the total number of messages sent in a market (see columns (1) and (2) in Table 3). This suggests comparing the proportion of exact and misleading messages across treatments will be key to test our *Reputation* hypothesis. The proportion of misleading messages per trader was indeed almost two times higher in the *Chat-no reputation* treatment (21.9%) than in the *Chat* treatment (12.3%), and this difference is significant (see column (5) in Table 3). Analogously, the proportion of exact messages was significantly higher in the *Chat* treatment than in the *Chat-no reputation* treatment (see column (4)).

It is possible that messages classified as misleading (informative) were intended to be informative (misleading) by the message senders. In particular, this might apply to traders who possess low cognitive skills and, therefore could not accurately infer other traders' information and, consequently, the true asset value from market prices (Hefti, Heinke and Schneider, 2016; Corgnet, DeSantis and Porter, 2018). However, Table 4 shows that the release of misleading messages cannot be predicted by cognitive skills, CRT and TOM scores, which have been identified as key to trading success in experimental markets (Hefti, Heinke and Schneider, 2016; Corgnet, DeSantis and Porter, 2018).

Table 3. Exact, Misleading and Informative Messages across Treatments per Trader

This table reports the average number of messages sent per trader across all markets. An exact message is one in which traders state their private signal. A misleading message is one in which traders state a message that contradicts the true asset value. We do not include a column with informative messages as it could simply be obtained by the difference between (1) and (3). Standard deviations are reported in parentheses.

Treatment	Total Number Messages (1)	Total Number Exact Messages (2)	Total Number Misleading Messages (3)	Proportion Exact Messages (4)	Proportion Misleading Messages[26] (5)
Chat	38.385 (52.096)	26.938 (36.471)	7.281 (22.177)	80.671% (25.709%)	12.287% (19.547%)
Chat-no reputation	48.052 (66.551)	22.937 (38.524)	15.322 (43.016)	60.334% (34.893%)	21.875% (22.411%)
Treatment Differences[27]					
P-values	*0.266*	*0.463*	*0.107*	*<0.001*[28]	*0.002*

**p*-value<0.10, ***p*-value<0.05 and ****p*-value<0.01

According to our model, lying costs are the sole determinants of truth-telling behavior in the *Chat-no reputation* treatment. In Table 4 (columns (1) and (2)), we thus turn to an analysis of traders' messages. In particular, we assess the extent to which honesty, as measured using the four items of the HEXACO sincerity scale (Ashton, Lee and de Vries, 2014) (see Internet Appendix Section II.D),

[26] Because Table 3 reports averages at the trader level, the proportions in column (4) [5] are not necessarily equal to the ratio: column (2)/column (1) [column (3)/column (1)].
[27] These differences were assessed by calculating the *p*-values associated to the *Chat* Dummy variable in a linear regression with cluster-robust standard errors at the session level, using the variable described in the column header as the dependent variable. These results are robust to bootstrapping standard errors and to define the variables at the market period level rather than at the trader level.
[28] For columns (4) and (5), similar *p*-values are obtained when using a fractional logit regression instead of a linear regression.

can explain the release of misleading and exact messages. In our analysis, we control for CRT and TOM. We also control for individual prosociality using the elicitation task developed by Bartling et al. (2009) (see see Internet Appendix Section II.C). In line with our model, we find that traders who score higher on the honesty index release a higher proportion of exact messages and a lower proportion of misleading messages than those who score lower. However, prosociality does not affect the release of exact and misleading messages. This is consistent with the fact that in our markets releasing one's private signal might hurt other traders holding the same signal. Even after controlling for honesty, cognitive skills (TOM and CRT) and prosociality, we still report a negative (positive) effect of being a male on the proportion of exact (misleading) messages sent to other traders. This finding extends previous results in the deception literature, showing that males are more likely than females to lie, especially when it is for the sake of increasing their own payoff (see Capraro, 2018 for a meta-analysis), to a market environment in which we were able to control for a variety of possible confounding factors.

It is interesting to note that prosociality does affect traders' behavior in the chat platform as it tends to predict a higher level of filtering of others' messages (see columns (3) and (4) in Table 4). More specifically, prosociality predicts a higher level of filtering of traders who released at least one misleading message in a given market period (see column (5) in Table 4). This finding seems consistent with the punishment literature in public good games according to which prosocial individuals might sanction others' self-interested actions (Fehr and Gächter, 2000; 2002).[29]

[29] Unlike the public good literature, in our setup sanctioning others does not entail a monetary cost.

Table 4. Release of Exact and Misleading Messages as a Function of Trader Honesty, Cognitive Skills and Prosociality in the *Chat-no reputation* Treatment and Filtering Activities as a Function of Prosociality in the *Chat* Treatment

This table reports the results from fractional logit (columns (1) and (2)) and linear (columns (3), (4) and (5)) panel regressions with robust standard errors (reported in parentheses).[30] The number of observations corresponds to the number of markets times the number of traders (minus the number of instances in which a trader did not send a message for columns (1) and (2)).

Treatment	*Chat-no reputation*		*Chat*		
Dependent Variable	Proportion Misleading Messages	Proportion Exact Messages	Number Filters	Number Filters	Number Filters (of Misleading Traders)
	(1)	(2)	(3)	(4)	(5)
Intercept	-2.167***	1.325***	0.292	-0.154	-0.230
	(0.268)	(0.250)	(0.407)	(0.447)	(0.386)
Individual characteristics					
Standardized Honesty Index	-0.286**	0.317**	-	-	-
	(0.136)	(0.143)			
Standardized Prosocial Index	-0.062	0.252	0.243**	0.316**	0.106**
	(0.144)	(0.182)	(0.123)	(0.136)	(0.054)
Standardized CRT Score	0.174	-0.111	0.396***	-	-
	(0.127)	(0.151)	(0.149)		
Standardized TOM Score	0.161	-0.153	0.029	0.064	0.016
	(0.151)	(0.173)	(0.104)	(0.136)	(0.013)
Male Dummy	1.143***	-1.246***	0.007	0.248	-0.030
	(0.278)	(0.313)	(0.239)	(0.260)	(0.111)
Market characteristics					
Market Number	0.018	-0.027**	0.075***	0.075***	0.032***
	(0.014)	(0.012)	(0.017)	(0.017)	(0.006)
True Value	0.001	-0.001	0.001	0.001	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
Observations	*n* = 1,406	*n* = 1,406	*n* = 1,632	*n* = 1,632	*n* = 1,632
Prob > χ^2	0.000	0.000	0.000	0.000	0.000
R^2	-	-	0.056	0.040	0.035

*p-value<0.10, **p-value<0.05 and ***p-value<0.01

[30] These results are mostly robust to considering a linear panel regression using cluster-robust standard errors at the session level (see Table A1 in Appendix A).

In addition, in the *Chat* treatment, a trader's "reputation" score suffered a large decline due to the release of misleading messages (see the negative and significant coefficient for *Proportion of Misleading Messages* in column (1) of Table 5). This means that filtering activities were indeed targeted at manipulative traders corroborating the idea that prosocial intentions might have driven them (as is shown in columns (3), (4) and (5) in Table 4).

Relatedly, we show that the release of misleading messages has a negative, although not significant, effect on traders' earnings in the *Chat* treatment, whereas it affects traders' earnings positively and significantly when filtering is disabled in the communication platform (*Chat-no reputation* treatment). This indicates that the ability to filter prevented asocial traders from engaging in profitable manipulation attempts at the expense of social (honest) traders.

Table 5. Traders' Reputation, Misleading Messages and Earnings

This table reports the results from linear panel regressions with robust standard errors (reported in parentheses).[31] A trader's reputation in a given market, calculated as: (11 - the number of times a trader was 'filtered' by another trader + the number of times a trader was 'unfiltered')/11, is regressed against the proportion of misleading messages the trader sent in that market and the trader's individual characteristics. The number of observations corresponds to the number of markets times the number of traders minus the number of instances in which a trader did not send a message. Traders' earnings are calculated for each market in cents.

Dependent Variable	Trader's Reputation	Trader's Earnings (in cents)	Trader's Earnings (in cents)	Trader's Earnings (in cents)
Treatment	*Chat*	*Chat*	*Chat*	*Chat-no reputation*
	(1)	(2)	(3)	(4)
Intercept	99.062***	1,009.141***	1,218.929***	1,168.705***
	(0.771)	(104.428)	(53.217)	(43.696)
Proportion of misleading Messages	-27.043***	-	-34.095	216.033***
	(2.717)		(57.534)	(42.727)
Trader's Reputation	-	2.115**	-	-
		(0.835)		
Individual characteristics				
Male Dummy	-1.144	-14.256	-18.844	-14.181
	(1.504)	(58.244)	(60.608)	(47.966)
Standardized CRT Score	0.524	97.062***	98.188***	52.956***
	(0.651)	(25.303)	(26.027)	(19.145)
Standardized TOM Score	0.393	62.492*	63.769*	-13.709
	(0.985)	(37.318)	(38.662)	(26.674)
Market characteristics				
Market Number	-0.411***	1.617	0.566	1.066
	(0.076)	(4.457)	(4.210)	(2.806)
True Value	0.004***	4.006***	4.015***	3.935***
	(0.001)	(0.096)	(0.094)	(0.140)
Observations	*n* = 1,481	*n* = 1,481	*n* = 1,481	*n* = 1,406
Prob > χ^2	0.000	0.000	0.000	0.000
R^2	0.360	0.717	0.712	0.718

*p-value<0.10, **p-value<0.05 and ***p-value<0.01

[31] These results are robust to considering session-clustered standard errors (see Table A2 in Appendix A) or bootstrapping of standard errors.

Finally, we assess the robustness of our results in a series of additional treatments (see Table 1 and Appendix B). First, we extended our main *Chat* treatment to the arguably more realistic case in which communication and trading occurred at the same time (*Chat-during*) as well as when traders were allowed to release free-form instead of fixed messages (*Free-form Chat*). In both treatments, informational efficiency was higher than under *No Chat* thus confirming the positive effect of chat on the informational efficiency of markets.

Next, we modified the structure of information to assess the robustness of our results to cases in which it was (i) difficult to determine if another trader was intentionally sending misleading messages to manipulate the market (*Chat-probabilistic* treatment) or (ii) very costly to reveal one's private signal (*Chat-insider* treatment). In the *Chat-probabilistic* treatment, private signals were correct with probability 80% (e.g., signal "Not 50" or "Not 490" is received when the true asset value is 240) and incorrect with probability 20% (e.g., signal "Not 240" is received when the true asset value is 240). We found that traders released their signals in a large majority of the cases and that the presence of chat improved informational efficiency compared to a baseline treatment with probabilistic signals. Similar findings were obtained in our insider treatments in which two of the twelve traders were fully informed of the true asset value while the remaining traders were left uninformed. Insiders released informative signals in the majority of the cases (75.8%) thus leading to an overall (although not statistically significant) improvement in informational efficiency compared to a no-chat baseline treatment with insiders.

Lastly, in two final robustness treatments (*Private Value-No Chat* and *Private Value-Chat-during*), we introduce mutual gains from exchange by assigning traders different values for the asset. In line with our previous findings, we report evidence for the positive effect of chat on the allocative efficiency of these markets as traders with a higher (lower) value for the asset were more (less) likely to hold shares in *Private Value-Chat-during* than in *Private Value-No Chat*.

5. Conclusion

Since the writings of Hayek (1945), economists have sought to understand better the mechanisms through which dispersed information is aggregated. In the many discussions regarding the informational and allocative efficiency of alternative mechanisms, comparisons have typically been made between decentralized markets and central planners. However, the role of decentralized communication in the well-functioning of markets has largely been ignored. Instead, experimental research in markets and personal exchange have been conducted in isolation (see Smith, 2007, for a review).

This gap in the literature seems increasingly difficult to justify, given the advent of new technologies facilitating decentralized communication among market participants. The apparent market panic associated with the recent shutdown of the Bloomberg market chat platform motivated us to study the impact of communication on the efficiency of markets. To that end, we used a laboratory market environment that allowed us to control for the flow of information and establish a causal link between the availability of a communication platform and the efficiency of markets. Our findings clearly show that communication platforms facilitate the transmission of private information across traders, thus ensuring the informational and allocative efficiency of markets. This was the case whether chat was performed before or during the market and regardless of the type of messages. Our findings were also robust to alternative information structures and to cases in which gains from exchange were present. The effect of chat on the informational efficiency of markets was only reduced in the case of markets with a few insiders and numerous uninformed traders. This reduction in efficiency occurred despite a high level of truthful communication. Interestingly, even in this case, the presence of chat still seems to foster rather than hinder the transmission of information. These findings are in line with the idea that social relations are not a “frictional drag that impedes competitive markets” (Granovetter, 1985, p. 482).

In addition, we identify lying costs and reputational concerns for honesty as key motivating factors behind the sharing of one’s own private information. We were able to separate these two motives for truth-telling by either displaying a trader’s “reputation” score on participants’ screens (*Chat* treatment) or not (*Chat-no reputation* treatment). Our work shows that designing social-interaction institutions to leverage social motives can promote the efficiency of markets. Because markets are embedded in a social context, our work stresses that market designers should take into account the very social motives which are often deemed to be only relevant to personal exchange (Smith, 1998, 2007; Sobel, 2009). This promising approach is what we refer to as *social market design*.

More generally, we can see our work and the emergence of social market design as a response to the recent call of Hirshleifer (2015) to develop the field of social finance and, more specifically, to study the interaction between economic and social institutions. Even though our lab study provides sharp results, we see our work as a first step in the analysis of the interaction between market-based and non-market exchanges. Further studies should assess the robustness of these findings and use what we have learned in the lab to develop targeted strategies to assess these questions in the field.

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7. Appendices

Appendix A. Additional Analyses of Main Treatments

Table A1. Release of Exact and Misleading Messages as a Function of Trader Honesty and Prosociality in the *Chat-no reputation* treatment

This table reports the results from linear panel regressions with cluster-robust standard errors at the session level (reported in parentheses).[32] The number of observations corresponds to the number of markets times the number of traders (minus the number of instances in which a trader did not send a message for columns (1) and (2)).

Treatment	*Chat-no reputation*		*Chat*		
Dependent Variable	Proportion Misleading Messages (1)	Proportion Exact Messages (2)	Number Filters (3)	Number Filters (4)	Number Filters (of Misleading Traders) (5)
Intercept	0.097***	0.789***	0.292	-0.154	-0.230
	(0.025)	(0.051)	(0.585)	(0.739)	(0.435)
Individual characteristics					
Standardized Honesty Index	-0.042*	0.072**	-	-	-
	(0.022)	(0.033)			
Standardized Prosocial Index	-0.006	0.057*	0.243	0.316*	0.106
	(0.019)	(0.034)	(0.161)	(0.174)	(0.068)
Standardized CRT Score	0.028	-0.021	0.396**	-	-
	(0.019)	(0.031)	(0.163)		
Standardized TOM Score	0.026**	-0.031	0.029	0.064	0.016
	(0.013)	(0.033)	(0.121)	(0.102)	(0.011)
Male Dummy	0.185***	-0.282***	0.007	0.248	-0.030
	(0.043)	(0.075)	(0.335)	(0.427)	(0.154)
Market characteristics					
Market Number	0.003*	-0.006*	0.075***	0.075***	0.032***
	(0.002)	(0.003)	(0.024)	(0.024)	(0.008)
True Value	0.001*	-0.001	0.001	0.001	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
Observations	*n* = 1,406	*n* = 1,406	*n* = 1,632	*n* = 1,632	*n* = 1,632
Prob > χ^2	0.000	0.000	0.000	0.000	0.000
R^2	0.081	0.115	0.056	0.040	0.035

*p-value<0.10, **p-value<0.05 and ***p-value<0.01

[32] We do not conduct fractional logit regressions as in Table 4 because it is not possible to estimate cluster-robust standard errors at the session level in that case.

Table A2. Traders' Reputation, misleading messages and earnings

This table reports the results from linear panel regressions with cluster-robust standard errors at the session level (reported in parentheses). A trader's reputation in a given market (calculated as: 11 minus the number of times a trader was 'filtered' by another trader + the number of times a trader was 'unfiltered') is regressed against the proportion of misleading messages the trader sent in that market and the trader's individual characteristics. The number of observations corresponds to the number of markets times the number of traders minus the number of instances in which a trader did not send a message. Traders' earnings are calculated for each market in cents.

Dependent Variable	Trader's Reputation	Trader's Earnings (in cents)	Trader's Earnings (in cents)	Trader's Earnings (in cents)
Treatment	*Chat*	*Chat*	*Chat*	*Chat-no reputation*
	(1)	(2)	(3)	(4)
Intercept	99.062***	1,009.141***	1,218.929***	1,168.705***
	(0.690)	(93.015)	(34.806)	(38.088)
Proportion of misleading Messages	-27.043***	-	-34.095	216.033***
	(3.065)		(43.725)	(46.189)
Trader's Reputation	-	2.115*	-	-
		(1.098)		
Individual characteristics				
Male Dummy	-1.144	-14.256	-18.844	-14.181
	(1.104)	(63.733)	(67.089)	(64.502)
Standardized CRT Score	0.524	97.062***	98.188***	52.956***
	(0.425)	(27.737)	(28.225)	(22.627)
Standardized TOM Score	0.393	62.492*	63.769*	-13.709
	(0.432)	(35.102)	(35.328)	(18.003)
Market characteristics				
Market Number	-0.411***	1.617*	0.566	1.066
	(0.184)	(0.974)	(0.755)	(0.644)
True Value	0.004	4.006***	4.015***	3.935***
	(0.003)	(0.021)	(0.019)	(0.071)
Observations	*n* = 1,481	*n* = 1,481	*n* = 1,481	*n* = 1,406
Prob > χ^2	0.000	0.000	0.000	0.000
R^2	0.360	0.717	0.712	0.718

**p*-value<0.10, ***p*-value<0.05 and ****p*-value<0.01

Appendix B. Robustness Checks

In this section, we provide numerous robustness checks by considering different types of chat (Section B.1), different structures of information (Section B.2) and different types of assets allowing for gains from exchange (Section B.3).

B.1. Alternative types of chat

For the sake of robustness and because markets and chat inevitably occur concurrently in actual stock exchanges, we conducted the *Chat-during* treatment in which market participants could communicate for the entire duration of each market period (but not prior to a market period). We also conducted a chat treatment in which participants could compose and send text messages for the duration of a market period (*Free-form Chat*). The goal of this treatment is to consider a communication environment that more closely resembles the 'Bloomberg Instant Messaging' platform. The free-form chat interface is similar to that of the fixed message treatments. One slight difference is that the pie chart (see top right corner of Figure 1) is not displayed because, unlike fixed messages, free-form messages could not easily be categorized into predefined groups (e.g., "Not 50", "Not 240" and "Not 490"). Otherwise, the design of *Free-form Chat* was identical to that of the main treatments (see Table 1).

Figure B1 displays the average price per minute per market period across all sessions for the following treatments: *No Chat*, *Chat-during* and *Free-form Chat* (see Internet Appendix Section I for graphs of transaction prices per market period for each individual session). The full set of instructions for all treatments is provided in the Internet Appendix Section IV.

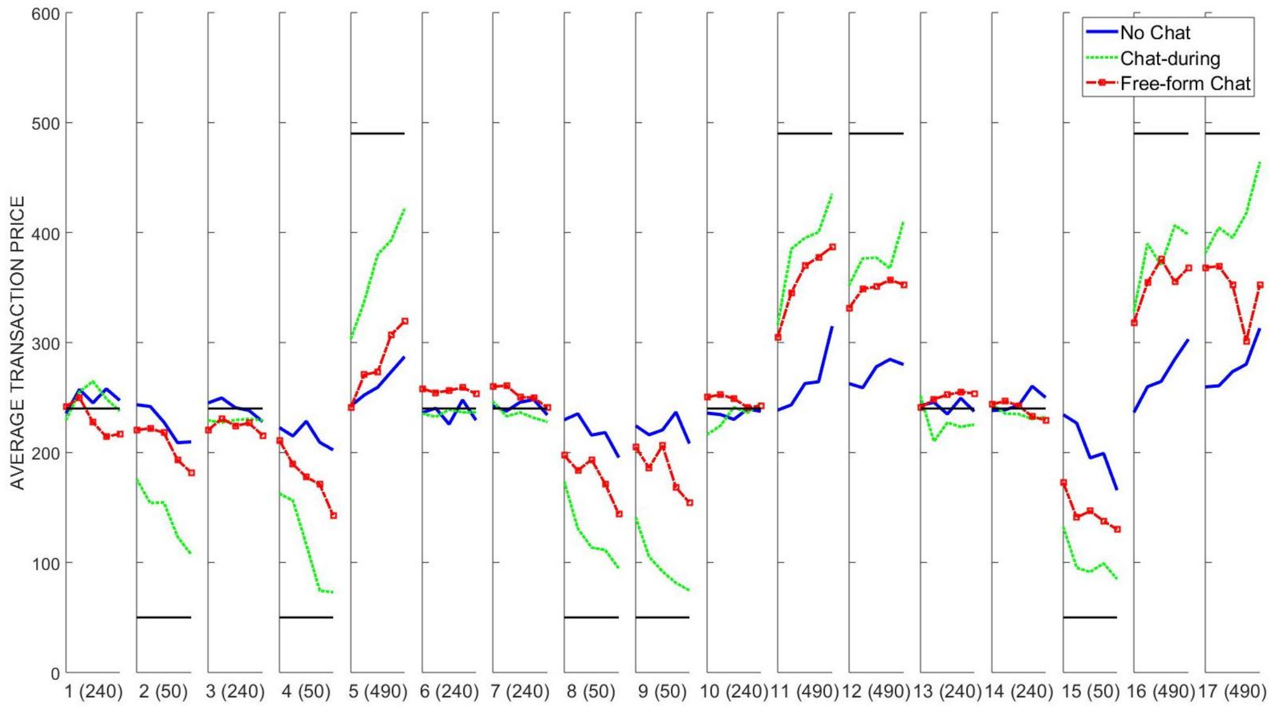

Figure B1. Average price per minute over the 10 *No Chat* sessions (solid blue curve), the eight *Chat-during* sessions (dotted green curve) and the eight *Free-form Chat* sessions (dash-dot red curve with square markers) for each of the 17 market periods. The true asset value is denoted at the bottom of each subfigure and displayed as a solid (black) horizontal line.

In line with Figure B1, we find that mispricing is significantly lower under *Chat-during* and *Free-form Chat* than under *No Chat* (see columns (1) through (4) Table B1) whereas the *Chat-during* and *Free-form Chat* treatments do not differ in terms of mispricing (see colmuns (5) and (6) in Table B2). However, *Chat-during* and *Free-form Chat* led to significantly more mispricing compared to *Chat* (see columns (1) through (4) in Table B2).

Table B1. Treatment Comparisons (*No Chat*, *Chat-during* and *Free-form chat*) for MAD Values per Market Period[33]

This table reports the results from linear panel regressions with random effects and cluster-robust standard errors at the session level (reported in parentheses). The number of observations corresponds to the number of sessions (18) multiplied by the appropriate number of market periods (three in specifications (1) and (3) and 17 in specifications (2) and (4)).

Sample	Chat During		Free Form Chat	
	Last Three Markets	All Markets	Last Three Markets	All Markets
	(1)	(2)	(3)	(4)
Intercept	-0.518	20.973**	50.998**	62.958***
	(11.325)	(8.885)	(23.149)	(12.016)
No Chat Dummy	109.347***	77.428***	46.975**	28.577***
	(16.647)	(7.984)	(22.680)	(9.920)
Market characteristics				
Market Number	-	-0.488	-	0.608
		(0.890)		(1.021)
True Value	0.105***	0.143***	0.147**	0.132***
	(0.042)	(0.026)	(0.057)	(0.031)
Observations	*n* = 54	*n* = 306	*n* = 54	*n* = 306
Prob > χ^2	0.000	0.000	0.000	0.000
R^2	0.440	0.276	0.159	0.093

**p*-value<0.10, ***p*-value<0.05 and ****p*-value<0.01

[33] Following Cameron and Miller (2011), we also estimated standard errors using the wild bootstrap procedure. The use of this procedure led to similar *p*-values.

Table B2. Treatment Comparisons (*Chat*, *Chat-during* and *Free-form chat*) for MAD Values per Market Period[34]

This table reports the results from linear panel regressions with random effects and cluster-robust standard errors at the session level (reported in parentheses). The number of observations corresponds to the number of sessions (16) multiplied by the appropriate number of market periods (three in specifications (1) and (3) and 17 in specifications (2) and (4)).

	Chat-during & Chat		Free-form & Chat		Free-form & Chat-during	
Sample	Last Three Markets (1)	All Markets (2)	Last Three Markets (3)	All Markets (4)	Last Three Markets (5)	All Markets (6)
Intercept	38.440***	60.821***	64.019***	90.991***	58.495**	79.896***
	(12.450)	(7.956)	(21.485)	(11.096)	(23.779)	(16.901)
Chat dummy	-30.104**	-22.052***	-62.372***	-48.851***	-	-
	(12.188)	(6.463)	(17.168)	(8.335)		
Chat-during dummy	-	-	-	-	-32.268	-26.799
					(22.052)	(18.334)
Market characteristics						
Market Number	-	-2.565***	-	-2.565***	-	-1.331*
		(0.670)		(0.859)		(0.678)
True Value	0.071*	0.147***	0.097*	0.134***	0.118***	0.134***
	(0.038)	(0.024)	(0.050)	(0.029)	(0.045)	(0.043)
Observations	$n = 48$	$n = 272$	$n = 48$	$n = 272$	$n = 48$	$n = 272$
Prob > χ^2	0.000	0.000	0.000	0.000	0.000	0.000
R^2	0.189	0.191	0.278	0.185	0.185	0.107

**p*-value<0.10, ***p*-value<0.05 and ****p*-value<0.01

[34] Following Cameron and Miller (2011), we also estimated standard errors using the wild bootstrap procedure. The use of this procedure led to similar *p*-values.

The *Chat-during* treatment differs from *Chat* because participants had to undertake two tasks (chatting and trading) simultaneously instead of sequentially. Thus, chat room participation was higher in the *Chat* treatment compared to *Chat-during* (see Table B3, column (1), Treatment Differences). It is thus important to compare truth-telling behavior in the two treatments using the proportion of exact and misleading messages (see Table B3, columns (4) and (5)) rather than the absolute number of messages (see Table B3, columns (2) and (3)). Doing so, we report that the proportion of exact (misleading) messages per trader was significantly lower (higher) in the *Chat-during* treatment compared to *Chat*.

A plausible explanation for these findings is that *Chat-during* may have induced additional cognitive load on participants which might have increased dishonesty compared to *Chat*. However, a recent meta-analysis (Verschuere et al. 2018) has demonstrated that truth-telling is not undermined by cognitive load. Finally, the *Chat-during* treatment might have weakened the honesty motives driving truthful communication by highlighting the possible tension between behaving cooperatively in the chat and competitively in the market (e.g., Cappelen, Sørensen and Tungodden 2013; Cohn, Fehr and Marechal, 2014; Falk and Szech, 2013; Bartling, Weber and Yao, 2015).

The negative effect of *Chat-during* on social motives for honesty seems to be large enough that it can offset the potential role of market orders (bids, asks and prices) as a disciplining mechanism for the release of manipulative messages. That is, misleading messages, which were inconsistent with current prices (e.g., submission of the "Not 490" message when prices are near 490) could have easily been identified, and senders of these messages could have been filtered. This could have dissuaded manipulative traders from attempting to distort market prices. Instead, we show in Table B3 that the proportion of misleading (exact) messages was significantly higher (lower) in the *Chat-during* treatment compared to *Chat*.

Table B3. Exact, Misleading and Informative Messages across Treatments per Trader

This table reports the average number of messages sent per trader across all markets. An exact message is one in which traders state their private signal. A misleading message is one in which traders state a message that contradicts the true asset value. A filter allows one trader to filter all messages sent to her by another trader. Standard deviations are reported in parentheses. For *Free-form Chat*, we also report the total number of messages which directly stated a signal (i.e., "Not 50", "Not 240", "Not 490", "50", "240", "490" see {signal-related messages} in column (1)).

Treatment	Total Number Messages **{**Signal-related Messages**}** (1)	Total Number Exact Messages (2)	Total Number Misleading Messages (3)	Proportion Exact Messages (4)	Proportion Misleading Messages (5)
Chat	38.385 (52.096)	26.938 (36.471)	7.281 (22.177)	80.671% (25.709%)	12.287% (19.547%)
Chat-during	24.542 (21.116)	14.781 (9.455)	7.094 (14.417)	69.669% (31.978%)	21.556% (24.860%)
Free-form Chat	24.063 (88.344) {5.322 (9.850)}	4.655 (9.000)	0.552 (1.534)	82.117% (29.838%)	12.673% (25.517%)
Treatment Differences[35]					
Chat vs. *Chat-during*	*0.017*	*0.002*	*0.945*	*0.010 [0.009]*	*0.005 [0.005]*
Chat vs. *Free-form Chat*	*0.173 [<0.001]*	*<0.001*	*<0.001*	*0.755 [0.756]*	*0.906 [0.905]*
Chat-during vs. *Free-form Chat*	*0.959 [<0.001]*	*<0.001*	*<0.001*	*0.014 [0.019]*	*0.007 [0.023]*

*p-value<0.10, **p-value<0.05 and ***p-value<0.01

Free-form Chat also led to higher mispricing than *Chat* (see columns (3) and (4) in Table B2). This could be partly explained by the fact that communication in the *Free-form Chat* treatment took place during trading which, as we have shown, tended to induce a higher proportion of misleading messages. Another effect attenuating the impact of this treatment on informational efficiency is that

[35] These differences were assessed by calculating the p-values associated to the treatment dummy corresponding to one of the two treatments being compared in a linear regression with cluster-robust standard errors at the session level, using the variable described in the column header as the dependent variable. These results are robust to bootstrapping standard errors and to defining variables at the market period level instead of at the trader level. In brackets, we report the p-values when using fractional logit regressions.

it led to many messages that were unrelated to private signals (see column (1) in Table B3). Despite these negative aspects, the proportion of exact messages (misleading messages) in *Free-form Chat* was at least as high (as low) as under *Chat* (see columns (4) and (5) in Table B3) and significantly higher (lower) than under *Chat-during*.

B.2. Structure of information

In previous treatments, telling the truth might have been especially conspicuous because deviating from the *truthful communication equilibrium* was unlikely to affect other traders' beliefs (see model in Appendix C). A lie which was released when all other traders told the truth could easily be spotted thus leading other traders to disregard this piece of information. This is the case because all but one message would be consistent with a given asset value. We thus check the robustness of our findings to a case in which spotting a liar would be less transparent. To that end, we consider a situation in which traders' private signals ("Not 50", "Not 240" or "Not 490") are only correct with probability 80%. In 20% of the cases, traders received the incorrect signal that the asset cannot take a value equal to the true asset value (e.g., receiving the signal "Not 240" when the true asset value is 240).[36] In this setup, traders do not know for sure whether they hold an accurate signal or not. In addition, traders cannot know whether another trader possesses the same signal. This implies that identifying a liar among traders telling the truth cannot be done with certainty as any signal would be consistent with telling the truth regardless of the messages sent by other traders. The full set of instructions for all treatments is provided in the Internet Appendix Section IV.

To assess the extent to which our previous findings are robust to this alternative structure of information, we compare truth-telling and informational efficiency in a treatment with chat (*Chat-probabilistic*), which was implemented in a manner consistent with our main *Chat* treatment, to a baseline (*No Chat-probabilistic*) (See Table 1). Replicating our previous findings, we show that most messages are truthful (80%) so that the proportion of exact messages does not differ between the *Chat-probabilistic* and the original *Chat* treatment (see column (5) in Table B5). In addition, less than 8% of the messages released were *misleading lies* which correspond to messages which differ from a trader's private signal and which are not consistent with the true asset value. In addition, chat

[36] Compared to the previous treatments, we also shortened each period by one minute and conducted a total of 10 markets instead of 17.

significantly increased the informational efficiency of markets when considering all market periods (see Table B4 for analysis of MAD and see Figures IA43 to IA52 in Internet Appendix Section I for the graphs of transactions prices for each individual session).

Table B4. Probabilistic Treatments Comparison for MAD Values per Market Period[37]

This table reports the results from linear panel regressions with random effects and cluster-robust standard errors at the session level (reported in parentheses). The independent variable, MAD, is computed with respect to the true asset value in specifications (1) and (2) and with respect to the Bayesian estimate in specifications (3) and (4). The number of observations corresponds to the number of sessions (10) multiplied by the appropriate number of market periods (three in specifications (1) and (3) and 17 in specifications (2) and (4)).

	True Value		Bayesian Estimate[38]	
Sample	Last Three Markets	All Markets	Last Three Markets	All Markets
	(1)	(2)	(3)	(4)
Intercept	119.907***	84.375***	57.324***	94.330***
	(11.623)	(10.111)	(17.776)	(10.363)
Chat Probabilistic Dummy[39]	-12.401	-15.359***	-7.095	-15.215***
	(9.453)	(4.820)	(5.972)	(5.164)
Market characteristics				
Market Number	-	8.615***	-	4.046***
		(1.244)		(1.130)
True Value	0.161***	0.078**	0.324***	0.068*
	(0.040)	(0.034)	(0.053)	(0.040)
Observations	n = 30	n = 100	n = 30	n = 100
Prob > χ^2	0.000	0.000	0.000	0.000
R^2	0.105	0.126	0.746	0.088

*p-value<0.10, **p-value<0.05 and ***p-value<0.01

[37] Following Cameron and Miller (2011), we also estimated standard errors using the wild bootstrap procedure. The use of this procedure led to similar p-values.

[38] This uses the Bayesian estimate of the true asset value rather than the true value to estimate MAD values via equation (1). This estimate is calculated assuming all private signals are known to all traders.

[39] This dummy takes value one for the *Chat-probabilistic* sessions.

Table B5. Exact, Misleading and Informative Messages across Chat and Chat-probabilistic Treatments per Traders

This table reports the average number of messages sent per trader across all market periods. An exact message is one in which traders state their private signal. A misleading message is one in which traders state a message that contradicts the true asset value, while a misleading lie is a message which contradicts the true asset value and does not correspond to the trader's private signal. We do not include a column with informative messages as it could simply obtained by the difference between (1) and (3). Standard deviations are reported in parentheses.

Treatment	Average Number Messages[40] (1)	Average Number Exact Messages (2)	Average Number Misleading Messages (3)	Average Number Misleading Lies (4)	Proportion Exact Messages (5)	Proportion Misleading Messages (6)	Proportion Misleading Lies (7)
Chat	2.258 (3.080)	1.830 (2.464)	0.428 (1.311)	0.428 (1.311)	80.671% (25.709%)	12.287% (19.547%)	12.287% (19.547%)
Chat-probabilistic	1.595 (1.361)	1.210 (0.961)	0.365 (0.550)	0.152 (0.314)	79.798% (27.904%)	20.682% (15.029%)	7.650% (10.137%)
<u>Treatment Differences</u>[41]							
P-values	*0.068*	*0.029*	*0.677*	*0.050*	*0.846* *[0.845]*	*0.003* *[0.004]*	*0.056* *[0.0046]*

**p*-value<0.10, ***p*-value<0.05 and ****p*-value<0.01

Another crucial feature of the information structure in our original treatments is that private information is highly dispersed so that the amount of information possessed by each individual trader is small. This was done purposefully to study the aggregation of fragmented information as envisioned by Hayek (1945). In that context, the impact of truthfully sharing one's private information on other traders' beliefs about the true asset value is limited. As a result, the cost of telling the truth, which follows from losing a trader's informational advantage with respect to those

[40] Because *Chat* and *Chat-probabilistic* had a different number of markets, we report average numbers of messages rather than total for the sake of comparison.

[41] These differences were assessed by calculating the *p*-values associated to the *Chat* Dummy variable in a linear panel regression with cluster-robust standard errors at the session level, using the variable described in the column header as the dependent variable. The market period number and the true asset value were added as control variables. In brackets are the *p*-values when using fractional logit instead of linear panel regressions. These results are robust to considering bootstrapping of standard errors.

who received a different private signal, is particularly small. By contrast, traders who are perfectly informed of the true asset value would have more to lose by releasing their private information to uninformed traders. Thus, an information structure in which a few insiders possess accurate information about the true asset value might limit truth-telling as well as the positive effect of chat on the informational efficiency of markets. To test this hypothesis we conducted treatments in which two of the twelve traders were fully informed of the true asset value while the remaining traders were left uninformed. We then compared insider treatments with chat (*Chat-insider*) and without chat (*No Chat-insider*) (see Figures IA53 to IA62 in Internet Appendix Section I for the graphs of each individual session). We found that truth-telling was still pervasive among insiders whose messages were in line with their private signals in 75.8% of the cases (see Table B6).

Table B6. Exact, Misleading and Informative Messages across Chat and Chat-Insider Treatments per Traders

This table reports the average number of messages sent per trader across all market periods. An exact message is one in which traders state their private signal. A misleading message is one in which traders state a message that contradicts the true asset value. We do not include a column with informative messages as it could simply obtained by the difference between (1) and (3). Standard deviations are reported in parentheses.

Treatment	Total Number Messages (1)	Total Number Exact Messages (2)	Total Number Misleading Messages (3)	Proportion Exact Messages (4)	Proportion Misleading Messages (5)
Chat	38.385 (52.096)	26.938 (36.471)	7.281 (22.177)	80.671% (25.709%)	12.287% (19.547%)
Chat-Two Insiders [insiders only][42]	7.100 (4.149)	5.000 (2.867)	2.100 (2.183)	75.763% (21.541%)	24.236% (21.541%)
<u>Treatment Differences</u>[43]					
P-values	*<0.001*	*<0.001*	*0.032*	*0.488* *[0.466]*	*0.083* *[0.045]*

**p*-value<0.10, ***p*-value<0.05 and ****p*-value<0.01

We also found chat to have a slight positive effect on informational efficiency although the decrease in mispricing was not significant (*p*-value = 0.242 for the *Chat* Dummy for the last three market periods, column (2) in Table B7).

[42] Numbers in brackets are calculated only for the two insiders in each market.

[43] These differences were assessed by calculating the *p*-values associated to the *Chat* Dummy variable in a linear panel regression with cluster-robust standard errors at the session level, using the variable described in the column header as the dependent variable. The market period number and the true asset value were added as control variables for the *p*-values reported in the first row. These results are robust to considering bootstrapping of standard errors.

Table B7. Insider Treatments Comparisons for MAD Values per Market Period[44]

This table reports the results from linear panel regressions with random effects and cluster-robust standard errors at the session level (reported in parentheses). The number of observations corresponds to the number of sessions (10) multiplied by the appropriate number of market periods.

Sample	Last Three Markets (1)	All Markets (2)
Intercept	86.980***	103.035***
	(15.741)	(84.713)
Chat Dummy	-6.936	-1.458
	(5.848)	(10.340)
Market characteristics		
Market Number	2.286***	-
	(0.247)	
True Value	0.154**	0.078**
	(0.068)	(0.034)
Observations	n = 30	n = 100
Prob > χ^2	0.011	0.000
R^2	0.093	0.126

*p-value<0.10, **p-value<0.05 and ***p-value<0.01

One reason mispricing did not substantially decrease in the *Chat-insider* treatment likely relates to the fact that although 96% of the insiders released at least one message, the total number of messages released was approximately five times lower (7.100 per trader) than in the *Chat* treatment (see column (1) in Table B6). In addition, non-insiders released a substantial number of messages (14.582 messages on average per trader) that might have limited the informational impact of insider messages. Indeed, the messages sent by non-insiders were largely random and thus not informative.[45]

In addition, we found that insiders earned more than non-insiders whether chat was present or not. However, the difference in earnings between insiders and non-insiders seemed to be less pronounced

[44] Following Cameron and Miller (2011), we also estimated standard errors using the wild bootstrap procedure. The use of this procedure led to similar p-values.

[45] We tested wether the distribution of messages of non-insiders for a given value of the asset was uniformly distributed. We could not reject the uniform distribution hypothesis when the true asset value was 50 or 490 (p-values = 0.643 and 0.158 for χ^2 tests) although this hypothesis was rejected when the true asset value was 240 (p-value < 0.001) in which case the proportion of "Not 490" messages was particularly high (52%).

in the presence of chat (see Table B8) although the interaction effect (Insider Dummy × *Chat* Dummy in column (3)) was not systematically significant across specifications. These results suggest some of the informational advantage of insiders might have disappeared due to the sharing of information in the chat platform, thus lowering the difference in earnings between insiders and non-insiders in the presence of chat.

Table B8. Traders' earnings of insiders and non-insiders

This table reports the results from linear panel regressions with robust standard errors (reported in parentheses). Traders' earnings are calculated for each market in cents. The Insider Dummy takes value one for a trader who was assigned the role of insider in a given market and value zero otherwise.

Dependent Variable	Trader's Earnings (in cents)		
Treatment	*Two Insiders*	*Chat-Two Insiders*	*Two Insiders & Chat-Two Insiders*
Treatment	(1)	(2)	(3)
Intercept	954.447***	1,149.532	1,110.685***
	(245.273)	(99.329)	(71.948)
Insider Dummy	349.837***	254.736***	349.680***
	(23.362)	(50.867)	(62.356)
Insider × *Chat* Dummy	-	-	-94.964[46]
			(80.219)
Chat Dummy	-	-	28.566
			(51.630)
Individual characteristics			
Male Dummy	69.368	34.000	46.248
	(84.260)	(63.565)	(52.907)
Standardized CRT Score	100.893***	12.747	44.688**
	(34.381)	(27.347)	(21.428)
Standardized TOM Score	1.946	48.475**	30.066
	(31.878)	(23.563)	(18.494)
Market characteristics			
Market Number	<0.001	<0.001	<0.001
	(3.938)	(4.504)	(2.976)
True Value	4.000***	4.000***	4.000***
	(0.263)	(0.244)	(0.178)
Observations	n = 1,020	n = 1,020	n = 2,040
Prob > χ^2	0.000	0.000	0.000
R^2	0.562	0.585	0.570

**p*-value<0.10, ***p*-value<0.05 and ****p*-value<0.01

[46] Using robust standard errors clustered at the session level, this variable is significant at the 1% level (p-value = 0.006) compared to a p-value = 0.236 for the current specification.

B.3. Gains from exchange

On average, fewer messages were sent (10.58 per each market period) than in the other chat treatments. However, a direct comparison across treatments is not meaningful as there were fewer market periods (10 instead of 17) and each market period was one minute (20%) shorter in the *Private Value-Chat-during* treatment compared to the other chat treatments. Importantly, the proportion of informative messages in the *Private Value-Chat-during* treatment reached 88.2% which is very similar to the *Chat-during* treatment (87.7%).[47] Consistent with our previous findings on the positive effect of trader communication on the informational efficiency of markets, we use these private values treatments to show that communication also fosters allocative efficiency.

To measure the allocative efficiency of a market in the private values treatments, we first compare the sum of asset payouts received by all traders in a given market (*Actual Payouts*) with the payouts that would have been made if traders knew the state of the world (*Max Payouts*). That is, when the state of the world is known, the group of six traders holding the lower value for the asset should sell its shares to the other six traders who would, on average, own six shares by the end of the market period. We calculate our first efficiency measure as:

$$Allocative\ Efficiency\ I \coloneqq Actual\ Payouts / Max\ Payouts$$

Following Plott and Sunder (1988), we also assess the extent to which a market allocation of shares improves upon the no-trade allocation. This is especially important given that the no-trade allocation allows traders to achieve close to 80% of the *Max Payouts*. We calculate our second efficiency measure as:

$$Allocative\ Efficiency\ II \coloneqq (Actual\ Payouts - Notrade\ Payouts)/(Max\ Payouts - Notrade\ Payouts)$$

where the *Notrade Payouts* are those obtained by traders when they keep their initial portfolio without making a trade. In line with the results reported in Plott and Sunder (1988), allocative

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[47] We report a p-value > 0.5 for the *Private Value-Chat-during* Dummy variable in a GLM regression of the proportion of informative messages per market period including data from this treatment as well as the *Chat-during* treatment. In addition to the *Private Value-Chat-during* Dummy variable, we included the market number, the true asset value, and the number of sent messages in a market as independent variables. Similar results are obtained when considering only the first ten market periods allowing for a more direct comparison between the *Private Value-Chat-during* treatment and the *Chat-during* treatment or when using linear panel regressions instead of GLM regressions.

efficiency is low for *Private Value-No Chat* (24.44%) even when considering the three market periods corresponding to the last occurrence of each state of the world. We show that allocative efficiency is higher in *Private Value-Chat-during* compared to *Private Value-No Chat*, regardless of the efficiency measure. The effect of communication is especially strong when considering the last occurrence of each of the three possible states of the world (see Last Three Markets of Table B9).

Table B9. Allocative Efficiency Measures

This table reports the values for the allocative efficiency measures corresponding to the private values treatments. Values either correspond to all ten markets in a session or to the last three markets that correspond to the last occurrence of each of the three possible states of the world [in brackets].

Treatment [Last Three Markets]	Allocative Efficiency I	Allocative Efficiency II
Private Value-No Chat	24.44% [24.44%]	82.45% [82.70%]
Private Value-Chat-during	33.33% [44.07%]	85.18% [87.61%]

In Table B10, we show that the introduction of communication (*Private Value-Chat-during* treatment) improves allocative efficiency compared to *Private Value-No Chat* when considering the last three occurrences of each state of the world because the coefficient of the *Private Value-Chat-during Dummy* variable is positive and significant (see columns (2) and (4) of Table B10).

Table B10. Allocative Efficiency of Chat Treatments

This table reports the results from linear panel regression with random effects and cluster-robust standard errors at the session level (reported in parentheses). For columns (1) and (3), the number of observations corresponds to the number of private values sessions (10) multiplied by the number of markets in each of these sessions (10). For columns (2) and (4), the number of observations corresponds to the number of private values sessions multiplied by three as these regressions only used the last three markets (from each session) that corresponded to the last occurrence of each of the three possible states of the world.

Dependent Variable	*Allocative Efficiency I*		*Allocative Efficiency II*	
Sample	All Markets	Last Three Markets	All Markets	Last Three Markets
	(1)	(2)	(3)	(4)
Intercept	0.121**	0.244***	0.156	0.208
	(0.060)	(0.083)	(0.103)	(0.154)
Private Value-Chat-during Dummy	0.089	0.196*	0.027	0.049**
	(0.107)	(0.117)	(0.017)	(0.022)
Market Number	0.022***	-	0.004***	-
	(0.008)		(0.001)	
Observations	n = 100	n = 30	n = 100	n = 30
Prob > χ^2	0.020	0.093	0.000	0.000
R^2	0.060	0.073	0.532	0.478

*p-value<0.10, **p-value<0.05 and ***p-value<0.01

Appendix C. Model

C.1. No-reputation model

To derive our hypotheses, we consider a *chat & trading* game with *n* players. As in our *Chat-no reputation* treatment, we assume chat and trading occur sequentially in two separate stages.

Following our experimental design, we consider a single risky asset whose true value (v) is modelled by a random variable (V) that can take one of three possible values $L < M < H$ with respective probabilities π_L, π_M, and $1 - \pi_L - \pi_M$. The distribution of the asset value is publicly known to each trader. Each participant is endowed with one unit of the asset and an amount of cash (C). We assume traders have enough cash to buy the asset so that $C \geq p$, where p is the price at which the asset is traded. Following our design, we assume all participants receive a signal $s_i \in \{\text{“Not L”}, \text{“Not M”}, \text{”Not H”}\}$ regarding one of the three values the asset cannot take. These signals are randomly distributed in the population of traders. In line with our experimental design, we assume at least two traders have the same signal. For a given asset value, we define the positive (negative) signal to be $s^+(s^-)$ when it leads to the highest (lowest) posterior estimate of the true asset value.

- In Stage 1 (*Chat*), given their private signal, players send a message, $m_i \in \{\emptyset, \text{“Not L”}, \text{“Not M”}, \text{“Not H”}\}$ for $i \in \{1, \dots, n\}$, to all other players.
- In Stage 2 (*Trading*), the asset can be traded. For the sake of illustration, we assume that a single trade can occur at a price *p*. We purposefully abstract away from the complex continuous double auction environment used in our experimental design. This allows us to derive hypotheses within a simple game-theoretic framework without relying on simulations.[48] In our setup, prices are exogenously set. A price is selected at random by a computer between the lowest and the highest possible asset valuations of traders. More specifically, *p* must satisfy $V_p^- \leq p \leq V_p^+$ where V_p^- (V_p^+) is the valuation of traders holding the negative signal (positive signal) given a transaction occurs at price *p*. Because there is a unique opportunity for trading, any traders holding the highest possible valuation for the asset will be willing to buy the asset at the proposed price whereas any trader holding the

[48] For continuous double auction models, see e.g., Copeland and Friedman (1987), Cason and Friedman (1986), or Friedman (1991).

lowest possible valuation will be willing to sell the asset at this price.[49] We focus on the analysis of *truthful communication equilibria* in which all traders send truthful messages and messages are believed to be truthful.[50] We assume risk neutrality so that traders maximize their expected earnings.[51] We start by considering the case of asocial traders who do not exhibit social preferences. We solve our chat & trading game by first analyzing trading in the second stage.

C.1.1. Asocial traders

Rational traders

In the case of asocial rational traders, no trade can occur in the second stage at a price which differs from the true asset value. This is the case because rational traders will only transact at a price p whenever the traders holding a negative signal are willing to sell to the traders holding a positive signal. This occurs when:

$$V_p^- \leq p \leq V_p^+ \Leftrightarrow E[V|v^+ \geq p, s^-; \boldsymbol{m}] \leq p \leq E[V|v^- \leq p, s^+; \boldsymbol{m}]$$

where $\boldsymbol{m} \coloneqq (m_1, \dots, m_n)$, $v^- \coloneqq E[V|s^-; \boldsymbol{m}]$, and $v^+ \coloneqq E[V|s^+; \boldsymbol{m}]$. However, this condition can only be satisfied when $E[V|v^+ \geq p, s^-; \boldsymbol{m}] = p = E[V|v^- \leq p, s^+; \boldsymbol{m}]$ which corresponds to the case in which the market price reveals all private information: $p = E[V|\boldsymbol{s}] = v$, where $\boldsymbol{s} \coloneqq (s_1, \dots, s_n)$. In that case, all traders are indifferent between buying and selling the asset at its true value. In equilibrium we thus have: $E[V|s^-; \boldsymbol{m}] = E[V|s^+; \boldsymbol{m}] = E[V|\boldsymbol{s}] = v$. It follows that sending messages in the first stage is irrelevant. This implies that truthful communication does not affect asset prices or traders' payoffs, because in the second stage all private information is transmitted to prices. Rational traders' best response to truthful messages in the first stage of the chat & trading game is to send either no message or any message. When all traders are rational,

[49] If several traders possess each signal, then one trader holding a positive signal will be randomly selected to trade with another randomly selected trader holding a negative signal. This random procedure can be seen as representing the random arrival time of traders.

[50] Note that our cheap-talk environment is simpler than the one described in Crawford and Sobel (1982) as the number of messages is finite and there are only two possible types of traders (who differ on the private signal they received). We also have a setting in which traders' types are correlated as different traders may receive the same signal. More generally, in our setting, receiving a specific signal affects the likelihood of other traders receiving a given signal.

[51] The risk-neutrality assumption becomes inconsequential when all private information is revealed by asset prices in which case the asset value can be directly inferred from the market price.

informational efficiency is thus achieved in the absence of communication, which trivializes the impact of the chat platform. We next consider the case of non-rational asocial traders.

Cursed traders

Corgnet, DeSantis, and Porter (2015) show that market prices may not reflect true asset value when the markets are populated with non-rational traders. This could result from the presence of noise (e.g., Grossman, 1977) or *cursed* (e.g., Eyster, Rabin, and Vayanos, 2018) traders. Given the emerging empirical support for cursed trading (e.g., Corgnet, DeSantis, and Porter, 2018), we consider the case in which traders' bounded rationality arises from their failure to infer other traders' private information from asset prices.[52]

In the spirit of Eyster, Rabin, and Vayanos (2018), conditional on observing the market price of the asset and a negative signal, cursed traders form expectations as follows:

$$E_{\chi}[V|v^{+} \geq p, s^{-}; \boldsymbol{m}] = (1-\chi)E[V|v^{+} \geq p, s^{-}; \boldsymbol{m}] + \chi E[V|s^{-}; \boldsymbol{m}],$$

where $\chi \in (0,1)$ determines the traders' level of cursedness. The higher the level of cursedness, the less private information traders infer from observing transaction prices. That is, traders assign less weight to $E[V|v^{+} \geq p, s^{-}; \boldsymbol{m}]$ when updating their beliefs. A similar expression holds for traders who received the positive signal:

$$E_{\chi}[V|v^{-} \leq p, s^{+}; \boldsymbol{m}] = (1-\chi)E[V|v^{-} \leq p, s^{+}; \boldsymbol{m}] + \chi E[V|s^{+}; \boldsymbol{m}]$$

Thus, in the case of cursed traders, trading can occur at prices which differ from the true asset value. In particular, trading can occur for any price in the following range:

$$(1-\chi)E[V|v^{+} \geq p, s^{-}; \boldsymbol{m}] + \chi E[V|s^{-}; \boldsymbol{m}] \leq p \leq (1-\chi)E[V|v^{-} \leq p, s^{+}; \boldsymbol{m}] + \chi E[V|s^{+}; \boldsymbol{m}]$$

However, a *truthful communication equilibrium* does not exist as any trader would have an incentive to deviate to obtain an informational advantage. This is the case because, unlike the case of rational traders, the market price does not convey the true asset value to traders. It follows that traders who deviate from the *truthful communication equilibrium* could effectively manipulate other traders' beliefs about the true asset value by sending a message that differs from their private signal. For example, a trader endowed with a negative signal will have an incentive to release a positive signal

[52] Corgnet, DeSantis, and Porter (2015) relate people's failure to infer others' private information from prices to low levels of cognitive reflection (see Frederick, 2005, as well as Toplak, West, and Stanovich, 2014). Thus, they refer to these cursed traders as non-reflective.

in order to raise other traders' beliefs about the true asset value. Indeed, in a *truthful communication equilibrium*, any message sent during the first stage is believed to be true. Thus, if trader *i* is endowed with the negative signal but sends the positive message, this will induce traders endowed with positive signals to hold a higher valuation of the asset than trader *i*, that is: $E_\chi[V|v^- \leq p, s^+; \boldsymbol{s_{-i}}, s_i^+] \geq E_\chi[V|v^- \leq p, s^+; \boldsymbol{s_{-i}}, s_i^-]$.

Because of the structure of information in the *Chat* treatment, distorting other traders' beliefs about the true asset value by deviating from the *truthful communication equilibrium* might be ineffective. This is the case because traders know for sure that other traders possess the same signal as theirs. It follows that if a trader endowed with a negative (positive) signal sends a positive (negative) signal message instead, then the number of negative (positive) signals reaching the market would be short one signal. This would inform other traders that a *truthful communication equilibrium* has not been reached in which case other traders' beliefs about the true asset value (after trader i's deviation) can be taken to be arbitrary.[53] However, the issue of pinning down off-equilibrium beliefs is resolved by the particular information structure implemented in the *Chat-probabilistic* treatment (see Appendix B.2). In that case, traders cannot know for sure whether other traders possess the same private signals as theirs. It follows that any distribution of messages would be consistent with a *truthful communication equilibrium* so that deviating from the equilibrium by lying would not require specifying off-equilibrim beliefs.

Anytime a trader's lie effectively impacts other traders' valuations it can potentially be profitable. In particular, the expected gains from trade of a trader endowed with the negative signal would be higher when releasing a positive rather than a negative message because this increases the maximum price traders endowed with the positive signal would be willing to pay for the asset (i.e., $E_\chi[V|v^- \leq p, s^+; \boldsymbol{m}]$).

In a market populated by cursed traders, it therefore follows that communication cannot be truthful as there exist incentives not to reveal one's private signal. In sum, in the presence of asocial traders, communication is either irrelevant (rational traders) or not truthful (cursed traders). We thus make

[53] However, the deviating trader might still possess an informational advantage in this case because (s)he will be the only trader who knows the true asset value with certainty.

the following hypothesis regarding the effect of communication on the informational efficiency of markets populated by asocial traders.

Hypothesis (Asocial traders) *In the presence of asocial traders, the ability to communicate does not improve the informational efficiency of markets*.

C.1.2. social traders

Following Abeler, Nosenzo and Raymond (2018) and Gneezy, Kajackaite and Sobel (2018), we assume social traders incur a direct cost of lying and reputational concerns. In this section, we focus on direct lying costs which we denote by φ.

To study the role of trader communication in the informational inefficiency of markets, we consider the case of cursed traders, who do not perfectly infer others' private information from prices. Unlike the case of asocial traders, when the market is populated with prosocial traders, there exists a *truthful communication equilibrium* that induces informational efficiency. This equilibrium exists because it is costly for prosocial traders to deviate from it. Deviating from the *truthful communication equilibrium* would allow a social trader to transact at a favorable price. However, this would imply lying, which is directly costly for a social trader.

Let us illustrate the cost of deviating from the *truthful communication equilibrium* by considering the case of fully-cursed prosocial traders ($\chi = 1$) when the asset value is low (i.e., $v = L$). Let us again consider a trader *i* who holds the negative signal and decides to deviate from the *truthful communication equilibrium* by releasing the most positive signal in order to raise other traders' beliefs regarding the true asset value. This would potentially allow the trader to then sell the asset at a more favorable price. The trader i who deviates will hold a more precise assessment of the asset value than any other trader in the market. When all other traders state their private signal truthfully, trader *i* will actually know the true asset value because her updated belief will be: $E^i_{\chi=1}[V|s_i;\boldsymbol{m}]= E[V|s^-;\boldsymbol{s_{-i}}] \coloneqq v$. By contrast, another trader *j* will hold more optimistic beliefs about the true asset value because: $V_p^+ \coloneqq E^j_{\chi=1}[V|s_j;\boldsymbol{m}]=E[V|s^+;\boldsymbol{s_{-i}}] \geq E[V|s^-;\boldsymbol{s_{-i}}] = v$, where $j \neq i$. This implies that trader *i* can now buy one unit of the asset from another trader *j* at any price between v and V_p^+. Thus, the expected utility of the fully-cursed prosocial trader who deviates from the *truthful communication equilibrium* is as follows:[54]

$$EU_{\chi=1,\varphi,\eta=0}^{i,d} := p - v - \varphi$$

where $p - v$ is the expected gain ($v - p$ is the expected loss) of trader i (j) from a transaction in which trader i sells the asset to trader j. As φ increases, it becomes costlier for a social trader to deviate from a *truthful communication equilibrium*. A prosocial trader will not deviate as long as:

$$EU_{\chi=1,\varphi,\eta=0}^{i,d} < EU_{\chi=1,\varphi,\eta=0}^{i^*} \Leftrightarrow \varphi > p - v \quad [1]$$

where $EU_{\chi=1,\varphi,\eta}^{i^*}$ is the expected utility of trader i when not deviating from the *truthful communication equilibrium*. In a *truthful communication equilibrium*, all traders know the true asset value so no trader can gain (lose) from a trade occurring at a price $p = v$. We thus have $EU_{\chi=1,\varphi,\eta=0}^{i^*} = 0$.

If we account for the additional costs of deviating from the *truthful communication equilibrium* related to reciprocal concerns, then the no deviation condition would be met for even lower lying costs φ.[55] Thus, we posit the following hypothesis.[56]

Hypothesis (Social traders) *In the presence of social cursed traders, communication leads to the release of truthful messages as long as direct lying costs are large enough, thereby promoting the informational efficiency of markets*.

[54] The cash endowment (C) is not included because it is irrelevant for these comparisons.

[55] In our model, truth-telling is exclusively sustained by honesty motives but it could more generally hinge on alternative mechanisms. For example, traders may reciprocate (e.g., Bolton and Ockenfels, 2000; Charness and Rabin, 2002) truth-telling from other traders by telling the truth (e.g., Abeler, Becker and Falk, 2014; Chen, Kartik and Sobel, 2008; Kajackaite and Gneezy, 2017). However, in our main *Chat* treatment other-regarding preferences (e.g., Andreoni, 1989; Rotemberg, 1994; Fehr and Schmidt, 1999; Andreoni and Miller, 2002; Bolton and Ockenfels, 2000; Charness and Rabin, 2002; Fehr and Fischbacher, 2003; Schmidt, 2011) will not play a role as telling the truth about one's own piece of private information will also harm those traders who already hold this piece of information by putting them at an informational disadvantage.

[56] A similar argument holds if we consider a market which is populated by a mix of social and asocial traders. In that case, we can show the existence of a *social-truthful communication equilibrium* in which social traders tell the truth whereas asocial traders do not send a message. Such an equilibrium improves the informational efficiency of the market because valuable information is obtained by cursed traders which could not have been inferred from observing market prices alone.

Thus far, we have assumed that the cost of being seen as a liar does not play a role in a trader's decision to truthfully communicate. In the next section, we study reputational concerns in addition to direct lying costs φ. We assume that social traders incur a fixed reputation cost (η) each time another trader identifies them as a liar with certainty.

C.2. Reputation model

We provide a model for the *Chat* treatment in which an individual "reputation" score is displayed on traders' screens. This "reputation" score depends on traders' decisions to filter others' messages. We thus add a stage to our no-reputation game in which traders will make a filtering decision after observing others' messages.

- Stage 1 (*Chat*) is the same as in the no-reputation model.
- In Stage 2 (*Reputation score*), participants can *filter* or not the messages of other participants, $f_{i,j} \in \{0,1\}$ where $i \neq j$. A player whose message is being filtered by $k \in \{0, \dots, n-1\}$ other players will have a publicly observable *score* equal to $r_i = \frac{n-1-k}{n-1}$.
- Stage 3 (*Trading*) is the same as Stage 2 in the no-reputation model.

Social traders are such that they incur a direct cost (φ) of lying and a fixed reputation cost (η) each time another trader identifies them as a liar with certainty.

In the reputation model, the set of *truthful communication equilibria* is enlarged compared to the no-reputation model. This is the case because *truthful communication equilibria* can exist even when direct lying costs are absent. These equilibria which we denote *reputation-truthful equilibria* occur whenever traders' filtering strategies reveal whether a trader is a liar with certainty. This equilibrium can be implemented when traders' strategies in Stage 2 are to filter a trader's message if it differs from their own message. This implies that a traders' lie which is not consistent with the true asset value will automatically lead all other traders to filter their messages thus obtaining the lowest possible "reputation" score. In that case, liars who state a message which is inconsistent with the true value will be identified with certainty. As long as being identified as a liar is sufficiently costly, a social trader will not deviate from telling the truth in equilibrium even if the direct cost of lying is zero. For the example studied in Section C.1 (i.e., $\chi = 1$ and $v = L$) in which a trader *i* who holds the negative signal decides to deviate from telling the truth in Stage 1 by releasing the most positive signal, the existence of a *reputation-truthful equilibrium* can thus be written as follows:

$$p - v - \varphi - q(n-1)\eta > 0 \qquad [2]$$

The term $q(n-1)\eta$ follows from the fact that by releasing the most positive signal, the trader deviating from the *reputation-truthful equilibrium* will release a message which might not be consistent with the true asset value. We define q as the probability that the message sent by the deviator is inconsistent with the true asset value. Note that q must be less than 1 in our setup because a trader might inadvertently release a message that is consistent with the true value although it differs from her private signal. In the case in which the deviating trader's message is not consistent with any of the signals held by the other traders, this trader will be identified with certainty as a liar by the other $(n-1)$ traders. By definition, this will entail reputation costs equal to $(n-1)\eta$.

As long as social traders care about their honesty reputation ($\eta > 0$), the condition of existence of *truthful communication equilibria* is less restrictive in the presence of "reputation" scores than in its absence (see condition [2]).[57]

Below we summarize our hypothesis regarding the impact of "reputation" scores on truth-telling.

Hypothesis (Social reputation) *In the presence of social cursed traders, the existence of a reputation score will facilitate the release of truthful messages compared to a case in which such a score is not available, thereby promoting the informational efficiency of markets*.

[57] It is also the case that any of the *truthful communication equilibria* which exist in the presence of a filtering stage also exist in its absence whenever filtering is uninformative in equilibrium as is the case, for example, if traders never filter others' messages in equilibrium.

Internet Appendix for "Let's chat… When communication promotes efficiency in experimental asset markets"

BRICE CORGNET, MARK DESANTIS and DAVID PORTER

This internet appendix includes a detailed description of the end-of-experiment survey tests and experiment instructions as well as figures of transaction prices per market period for each experimental session.

Contents

I. Market Figures

This appendix includes plots of transaction prices per market period. The average price per market period is listed at the top of each subfigure, and transactions are denoted by red dots. Figures IA1 through IA10 correspond to the *No Chat* sessions. Figures IA11 to IA18 correspond to the *Chat* sessions, Figures IA19 to IA26 correspond to the *Chat-no reputation* sessions, Figures IA27 to IA34 correspond to the *Chat-during* sessions, and Figures IA35 to IA42 correspond to the *Free-form Chat* sessions. The true asset value is denoted at the bottom of each subfigure and is also indicated by a solid horizontal line. Figures IA43 to IA47 correspond to the *No Chat-probabilistic* sessions, while figures IA48 to IA52 correspond to the *Chat-probabilistic* sessions. Both the Bayesian estimate of the asset value as well as the true asset value are denoted at the bottom of each subfigure (Bayesian estimate; True asset value). The true asset value is indicated by a solid horizontal line, while the Bayesian estimate is indicated by a dashed horizontal line. Figures IA53 to IA57 correspond to the *No Chat-insider* sessions, while Figures IA58 to IA62 correspond to the *Chat-insider* sessions. The true asset value is denoted at the bottom of each subfigure and is also indicated by a solid horizontal line. Figures IA63 to IA67 correspond to the *Private Value-No Chat* sessions, while Figures IA68 to IA72 correspond to the *Private Value-Chat-during* sessions. The true state of the world (X, Y, or Z) is denoted at the bottom of each subfigure. The true asset value is indicated by a solid horizontal line for one group of traders and a dashed horizontal line for the other group.

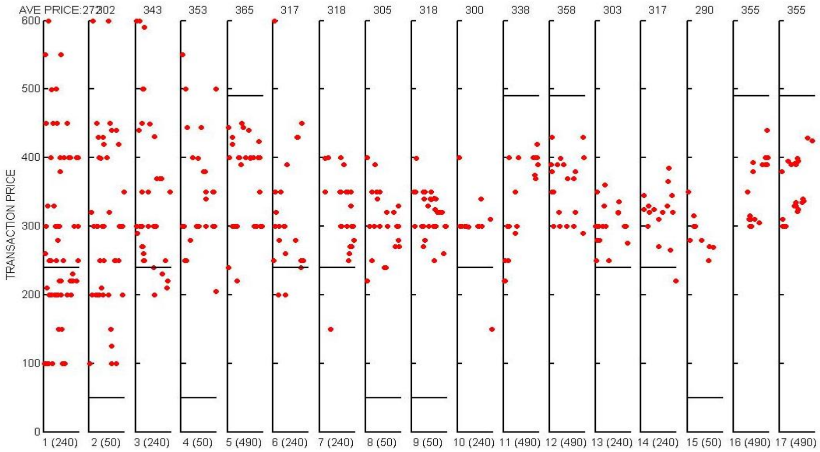

Figure IA1. *No Chat* Session 1.

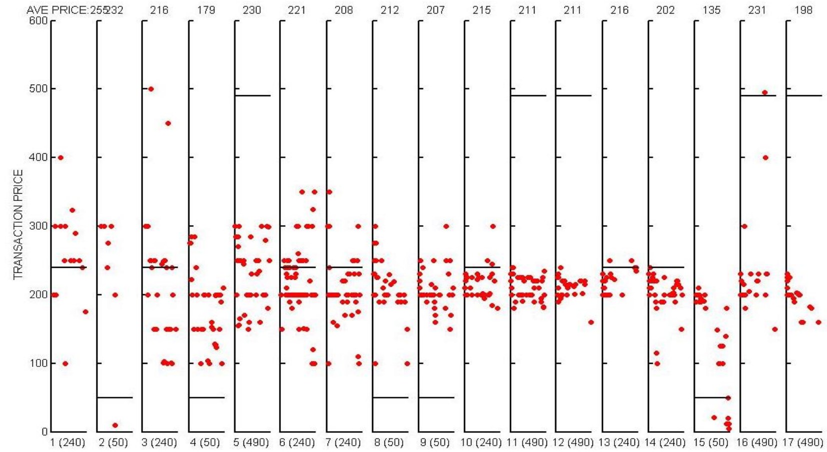

Figure IA2. *No Chat* Session 2.

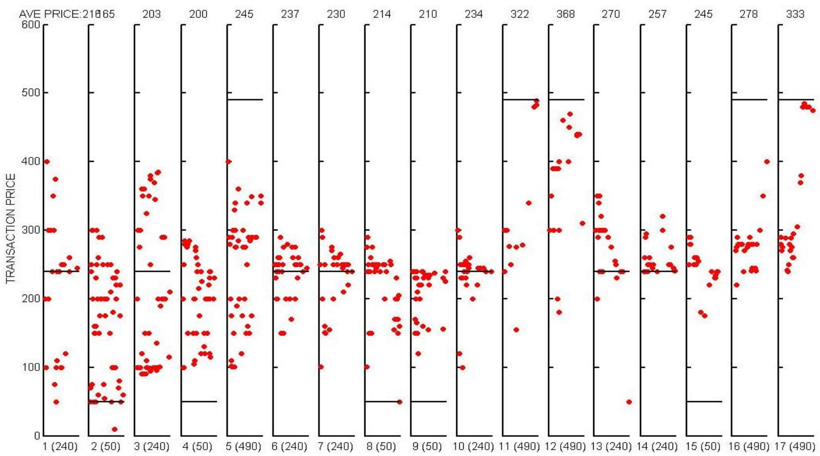

Figure IA3. *No Chat* Session 3.

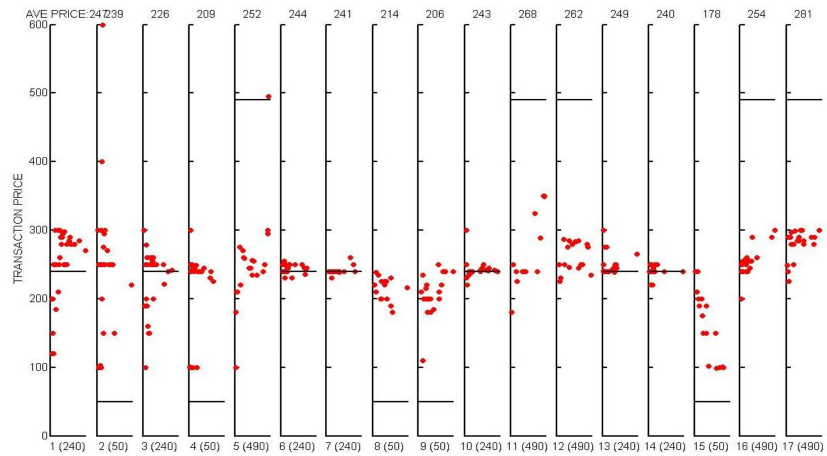

Figure IA4. *No Chat* Session 4.

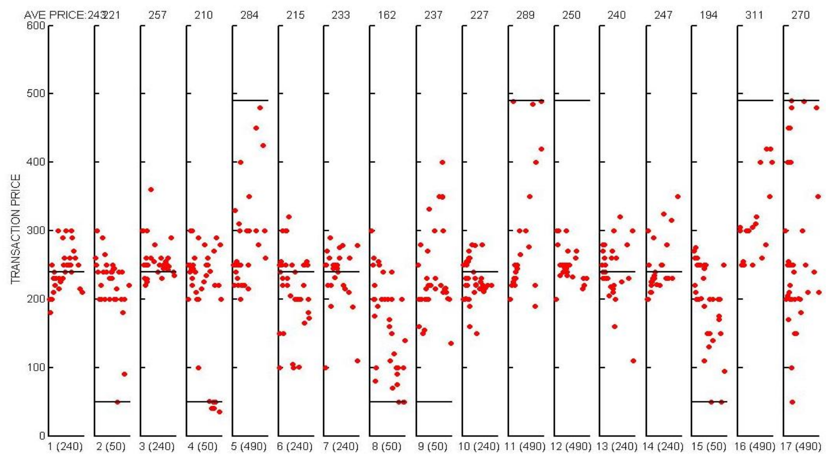

Figure IA5. *No Chat* Session 5.

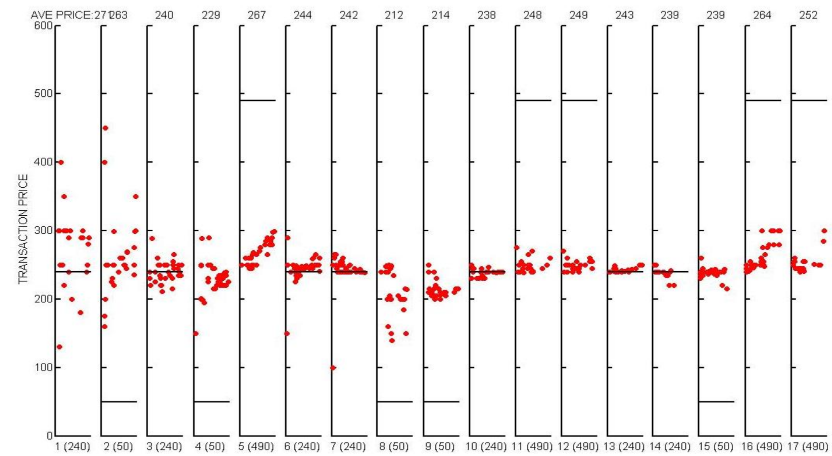

Figure IA6. *No Chat* Session 6.

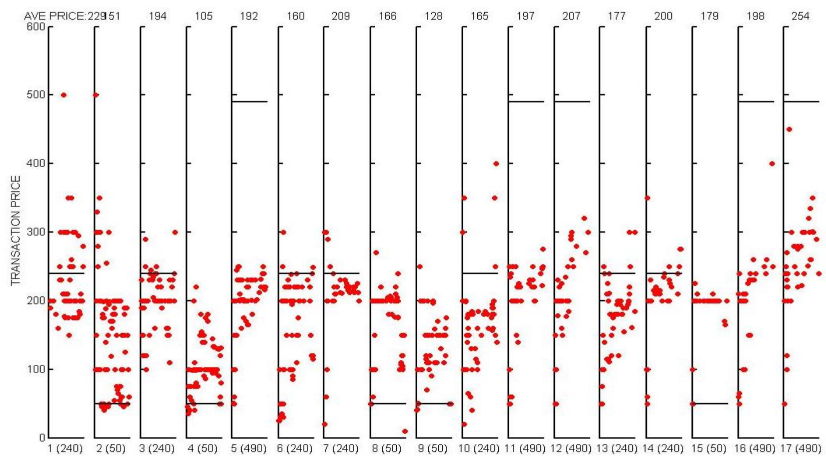

Figure IA7. *No Chat* Session 7.

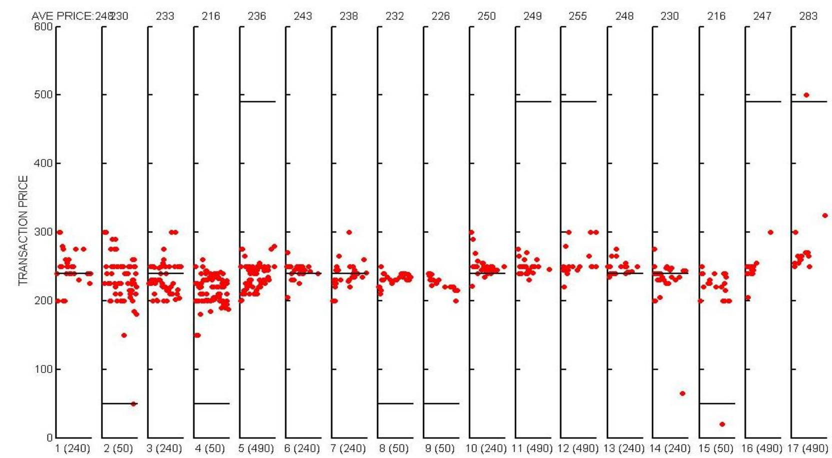

Figure IA8. *No Chat* Session 8.

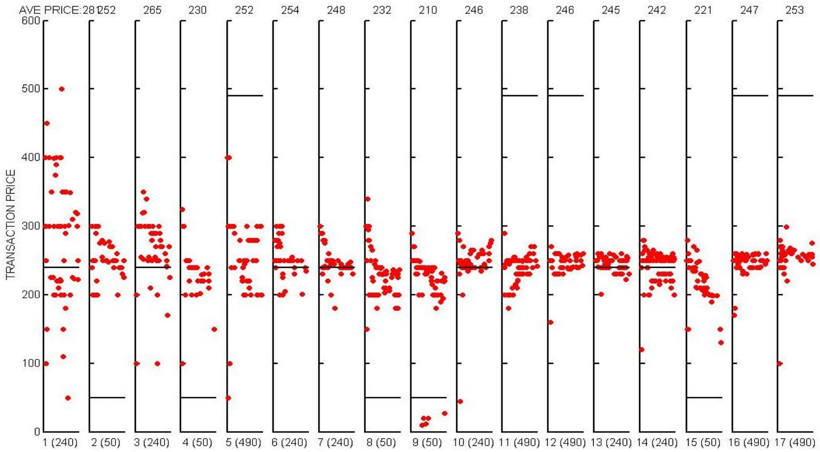

Figure IA9. *No Chat* Session 9.

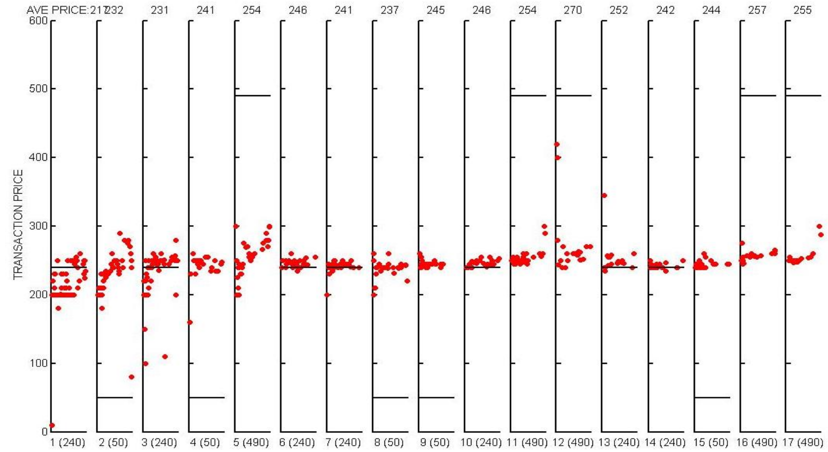

Figure IA10. *No Chat* Session 10.

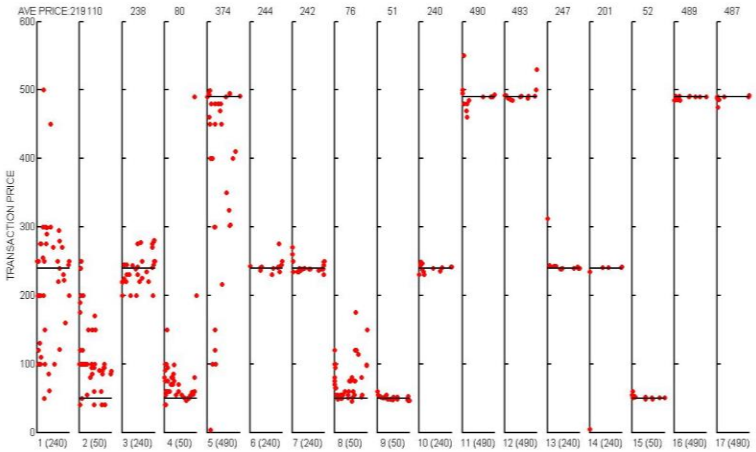

Figure IA11. *Chat* Session 1.

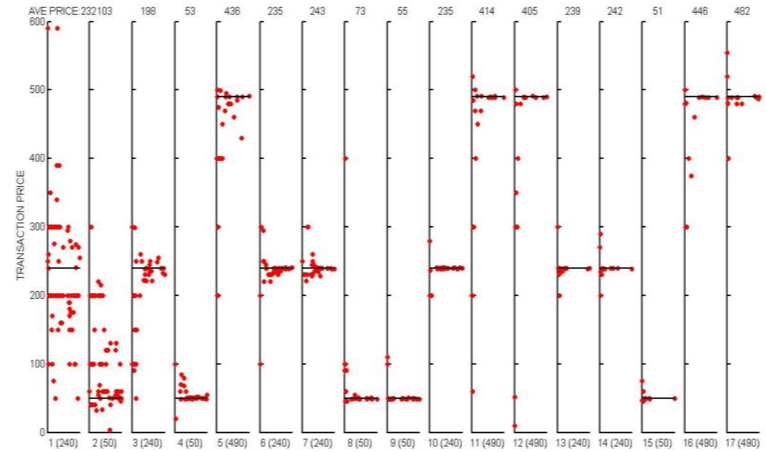

Figure IA12. *Chat* Session 2.

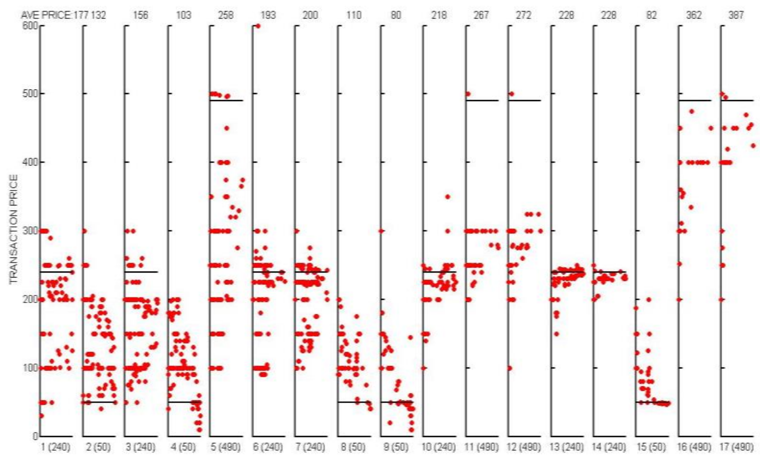

Figure IA13. *Chat* Session 3.

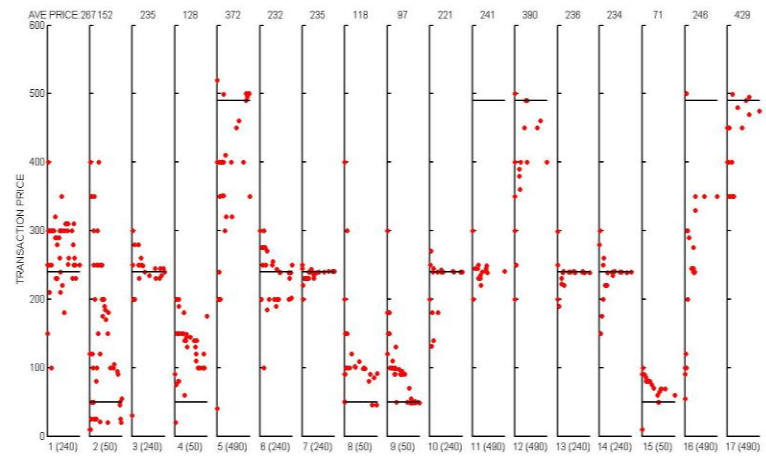

Figure IA14. *Chat* Session 4.

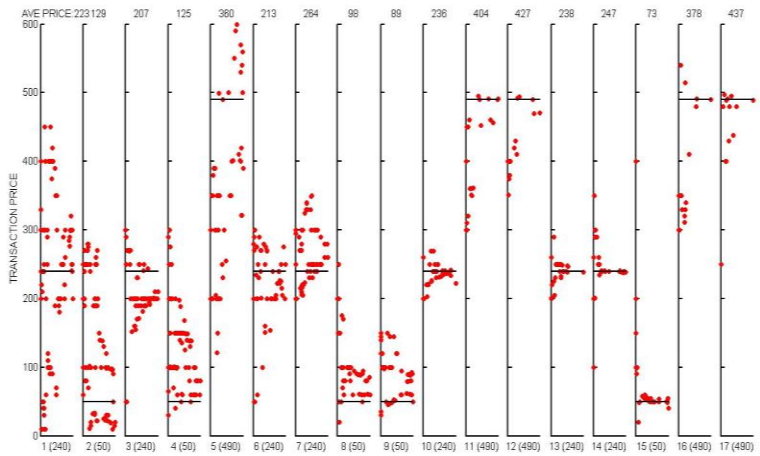

Figure IA15. *Chat* Session 5.

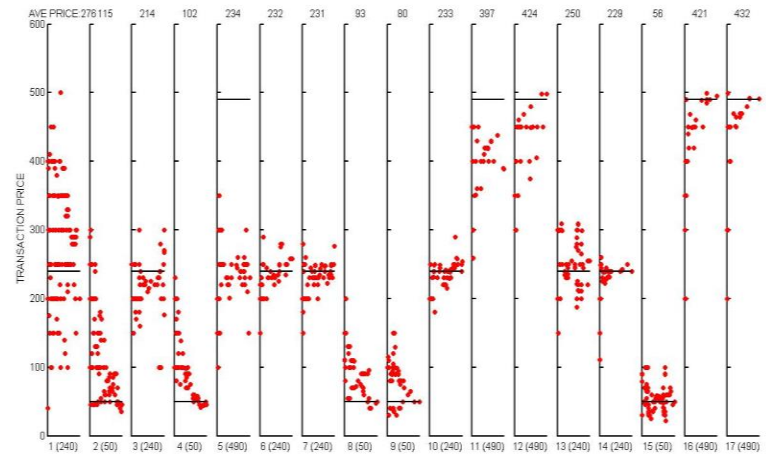

Figure IA16. *Chat* Session 6.

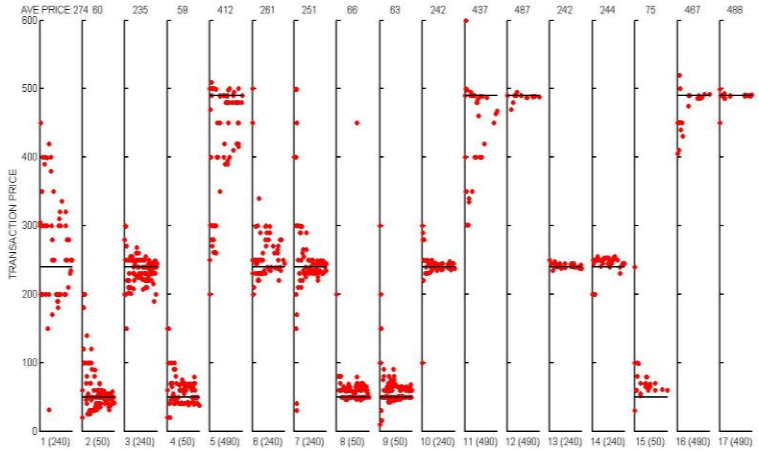

Figure IA17. *Chat* Session 7.

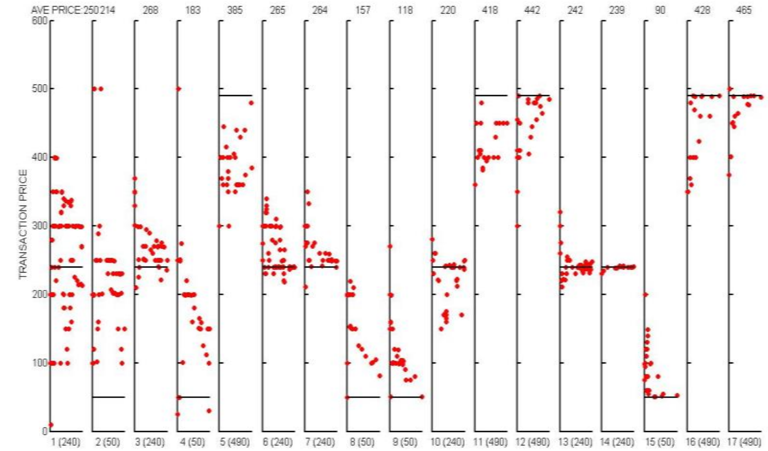

Figure IA18. *Chat* Session 8.

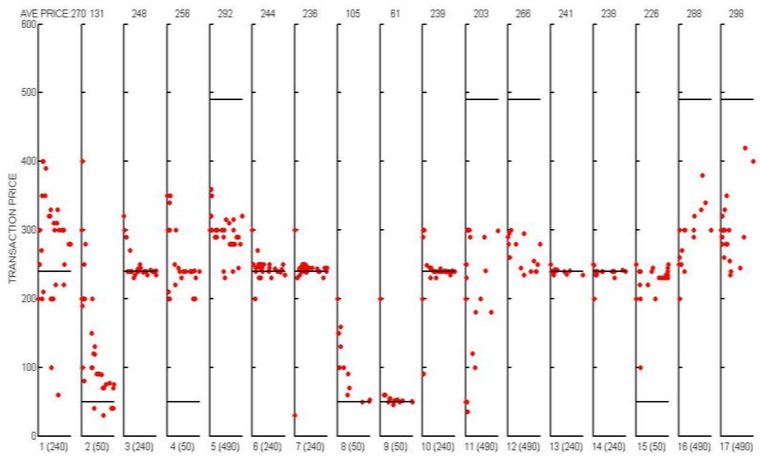

Figure IA19. *Chat-no reputation* Session 1.

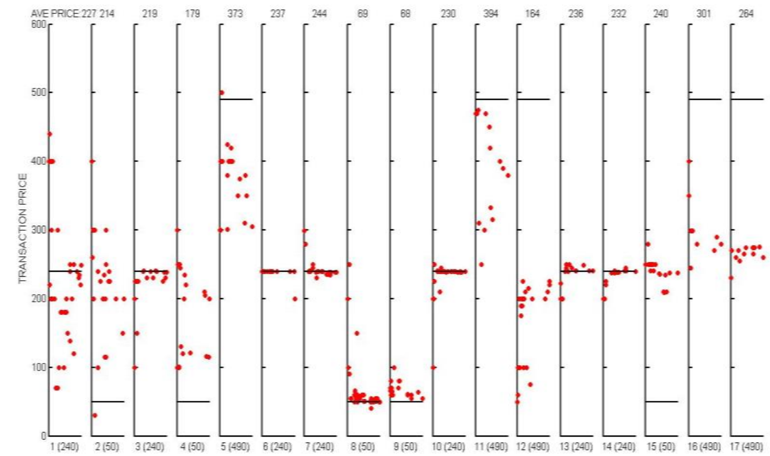

Figure IA20. *Chat-no reputation* Session 2.

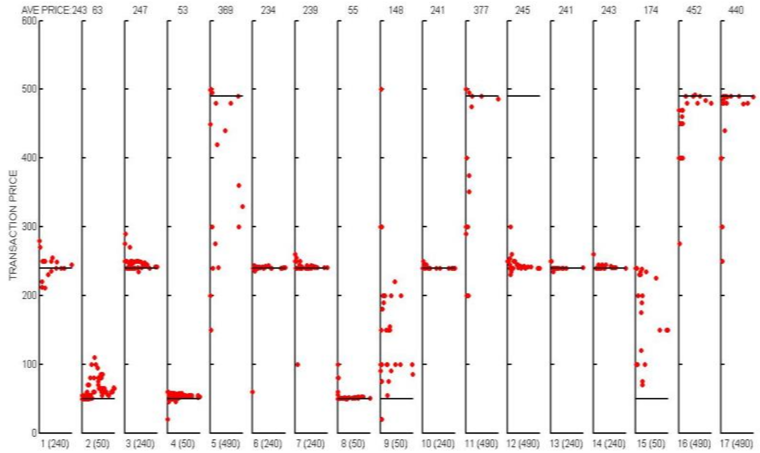

Figure IA21. *Chat-no reputation* Session 3.

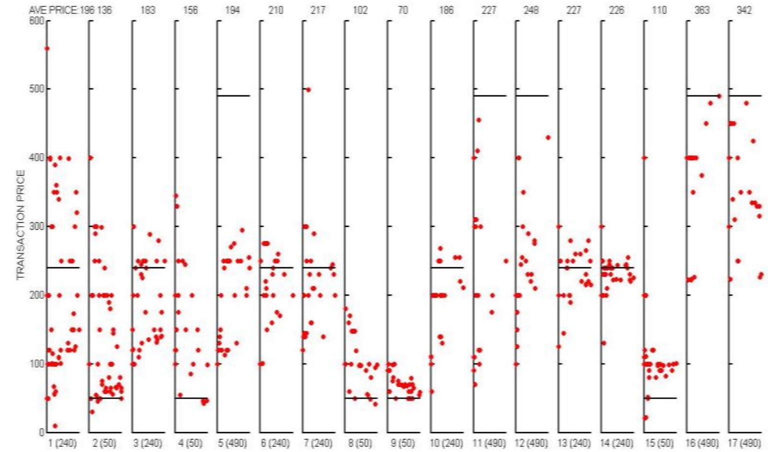

Figure IA22. *Chat-no reputation* Session 4.

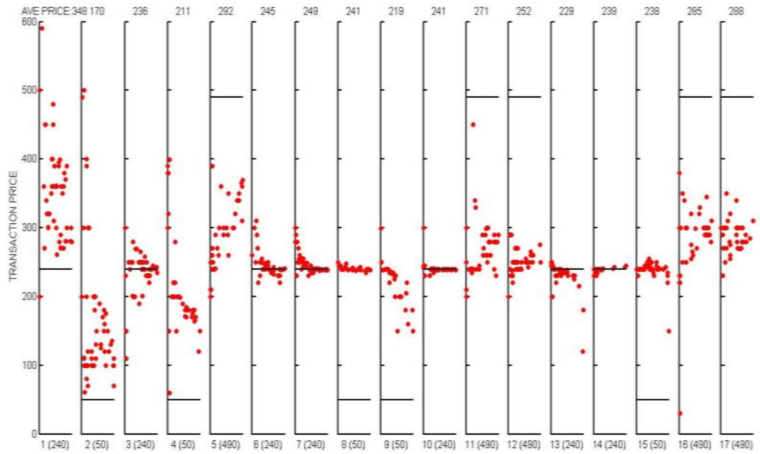

Figure IA23. *Chat-no reputation* Session 5.

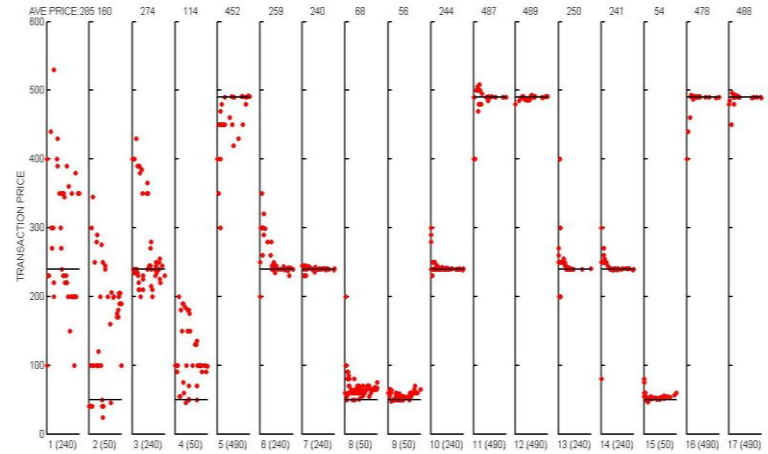

Figure IA24. *Chat-no reputation* Session 6.

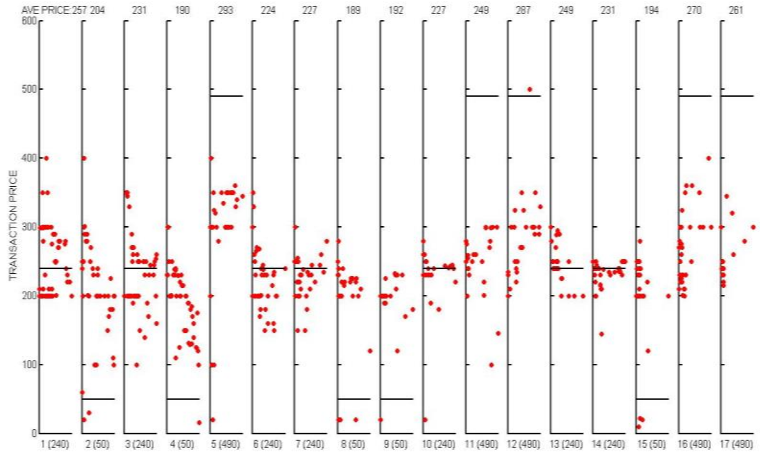

Figure IA25. *Chat-no reputation* Session 7.

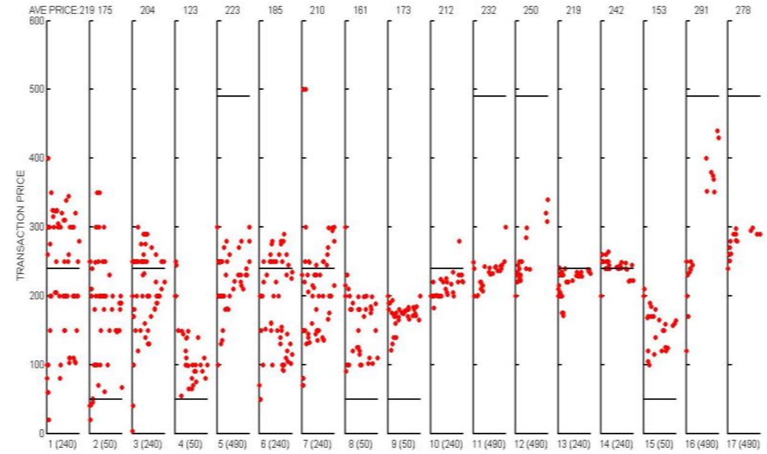

Figure IA26. *Chat-no reputation* Session 8.

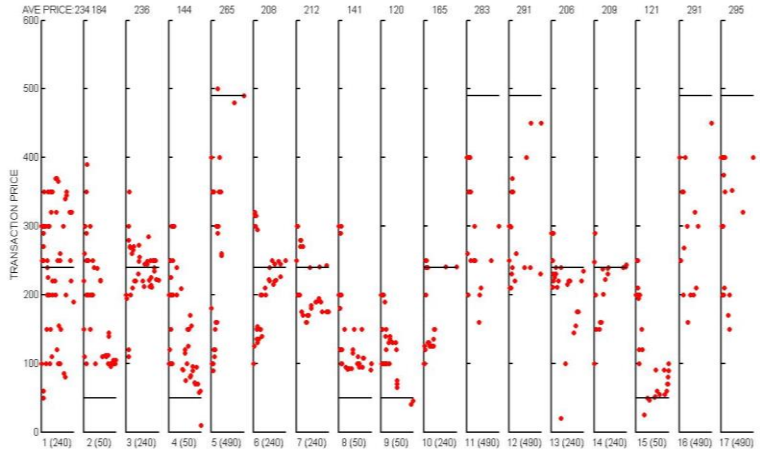

Figure IA27. *Chat-during* Session 1.

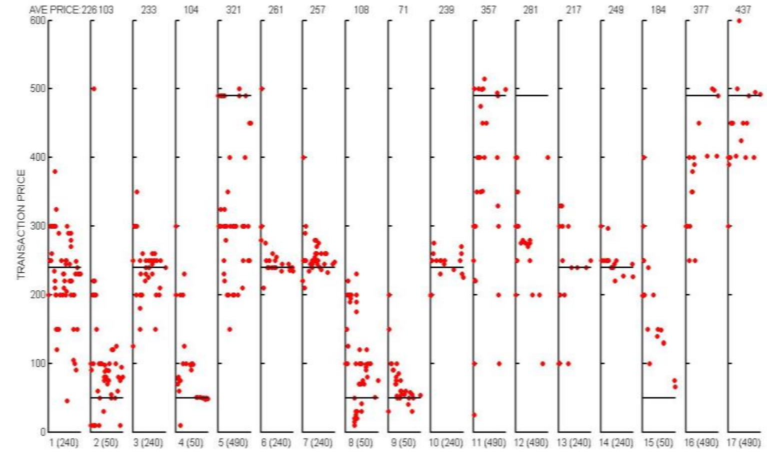

Figure IA28. *Chat-during* Session 2.

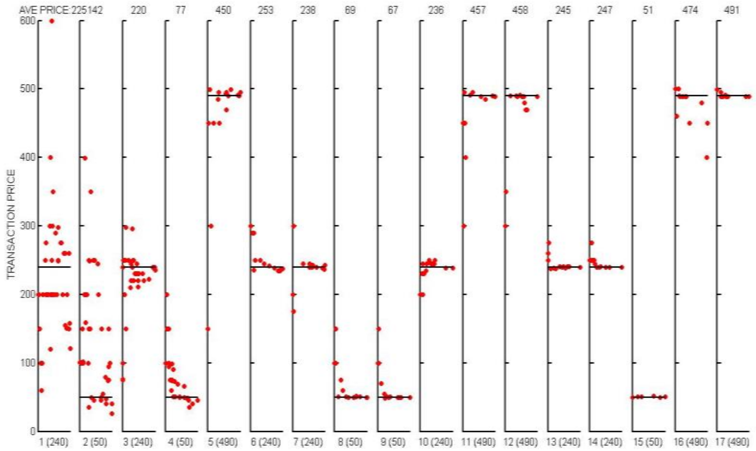

Figure IA29. *Chat-during* Session 3.

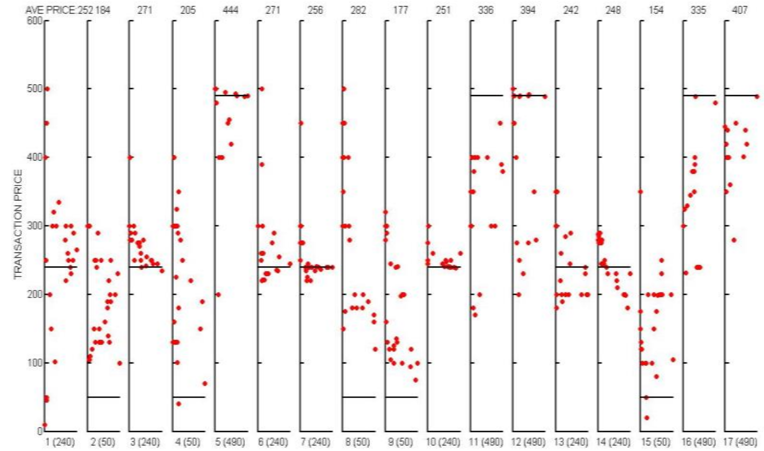

Figure IA30. *Chat-during* Session 4.

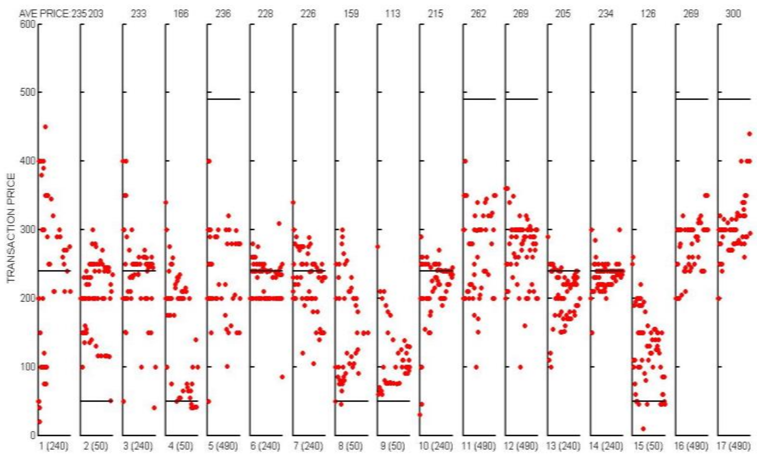

Figure IA31. *Chat-during* Session 5.

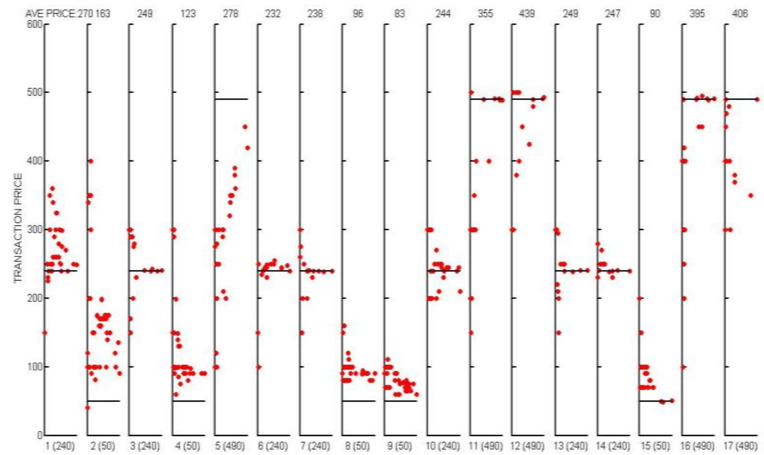

Figure IA32. *Chat-during* Session 6.

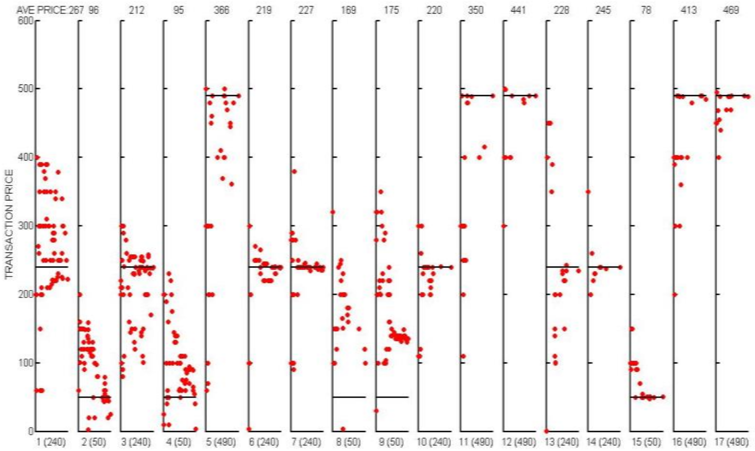

Figure IA33. *Chat-during* Session 7.

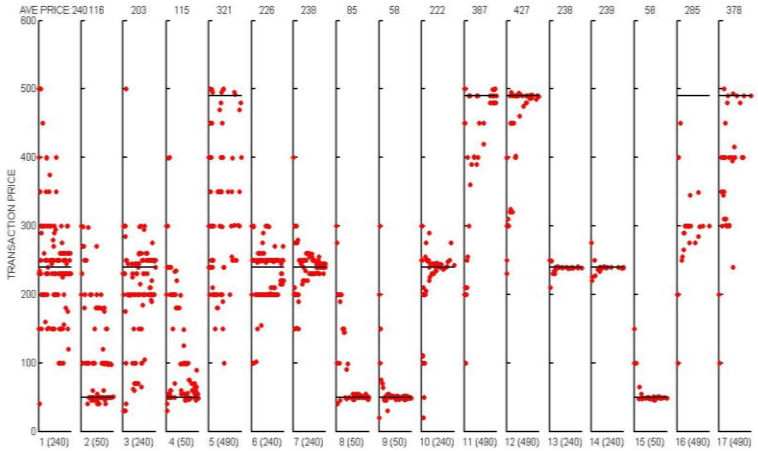

Figure IA34. *Chat-during* Session 8.

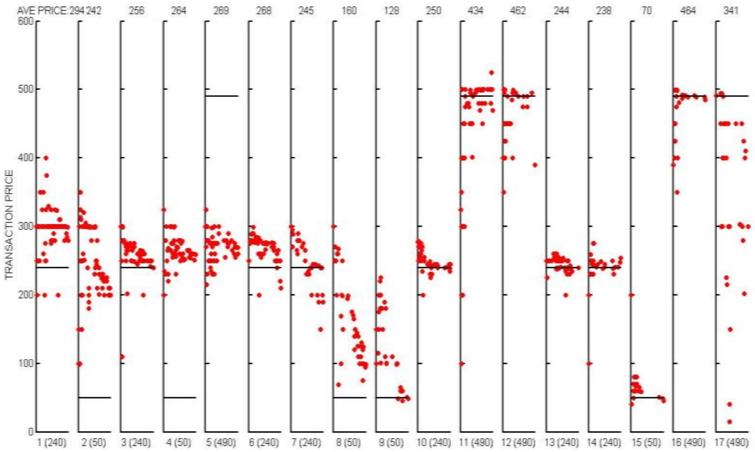

Figure IA35. *Free-form Chat* Session 1.

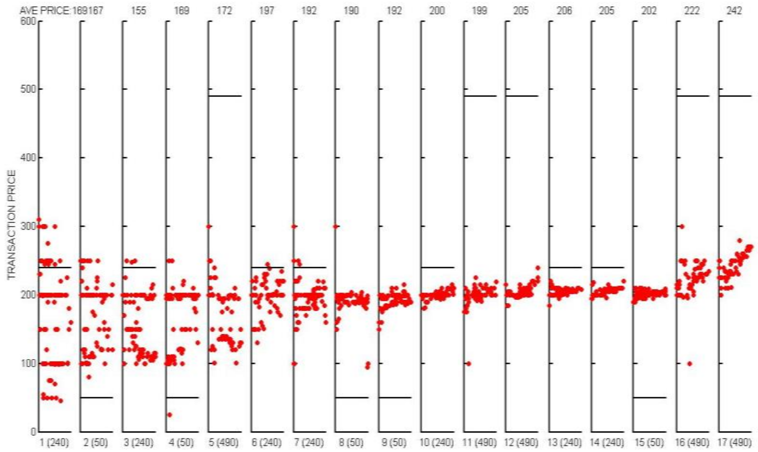

Figure IA36. *Free-form Chat* Session 2.

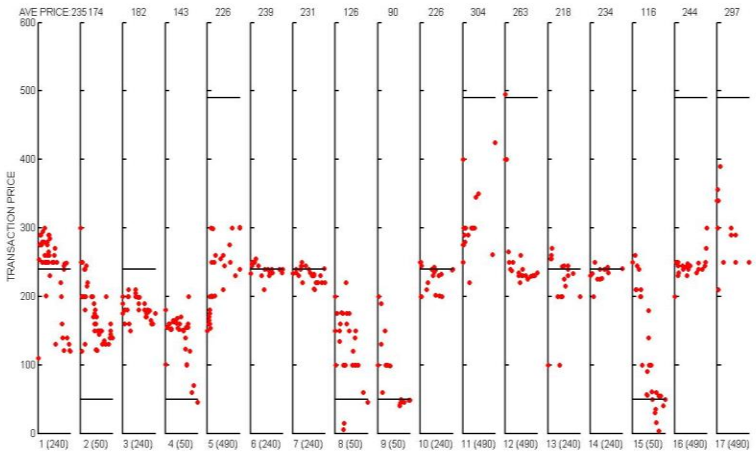

Figure IA37. *Free-form Chat* Session 3.

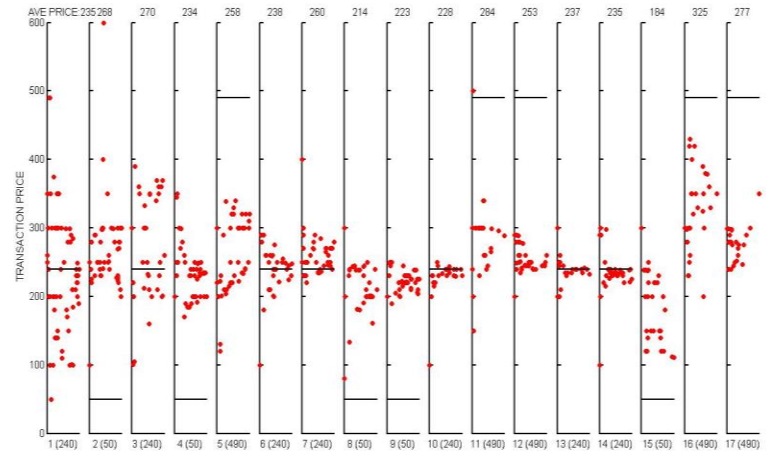

Figure IA38. *Free-form Chat* Session 4.

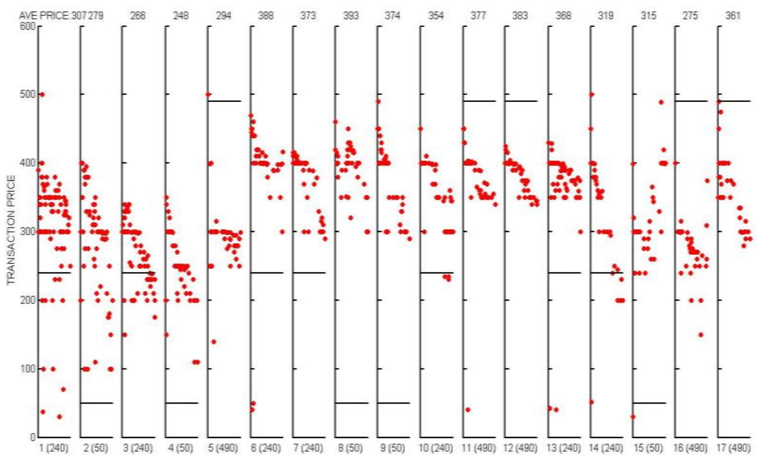

Figure IA39. *Free-form Chat* Session 5.

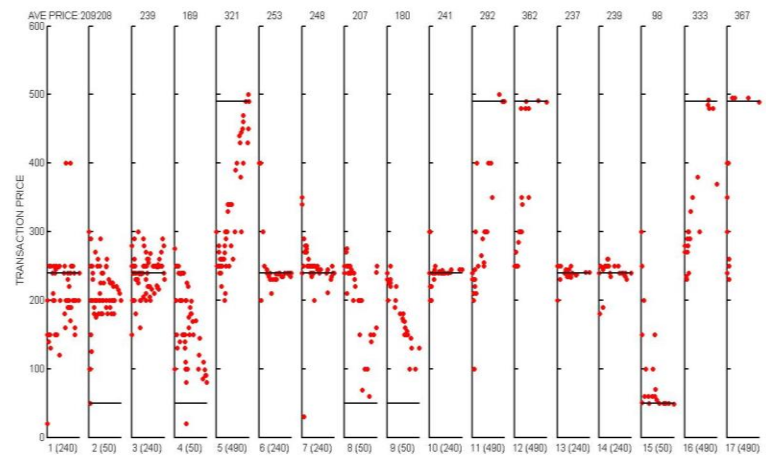

Figure IA40. *Free-form Chat* Session 6.

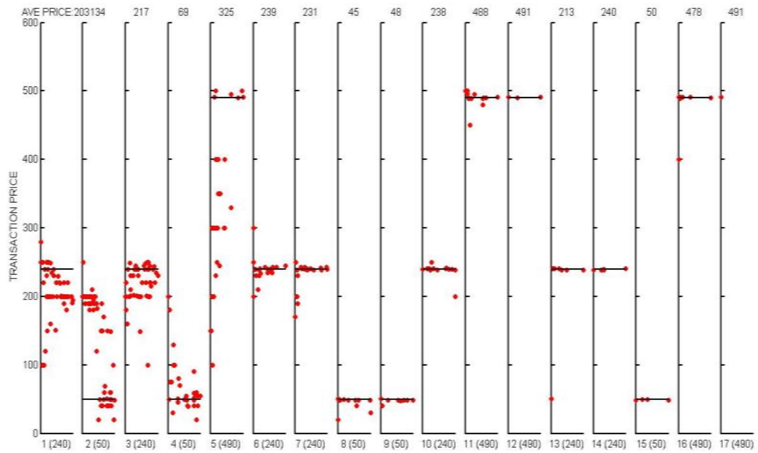

Figure IA41. *Free-form Chat* Session 7.

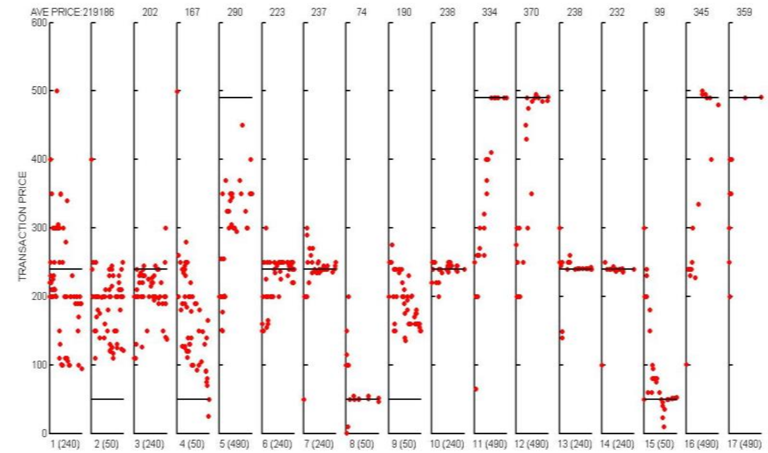

Figure IA42. *Free-form Chat* Session 8.

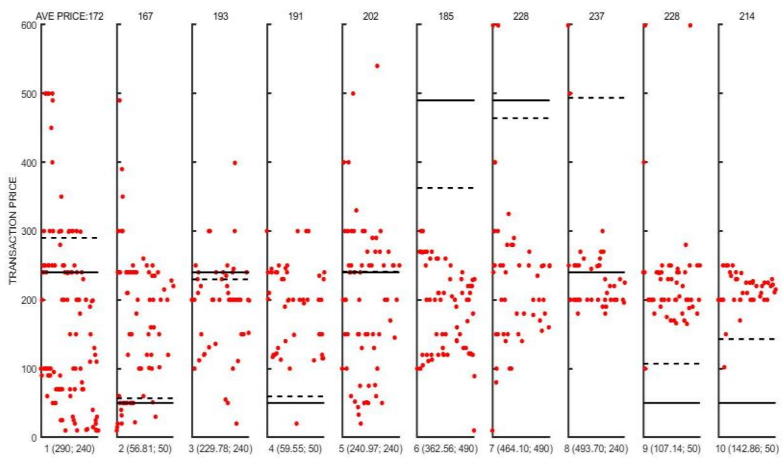

Figure IA43. *No Chat-probabilistic* Session 1.

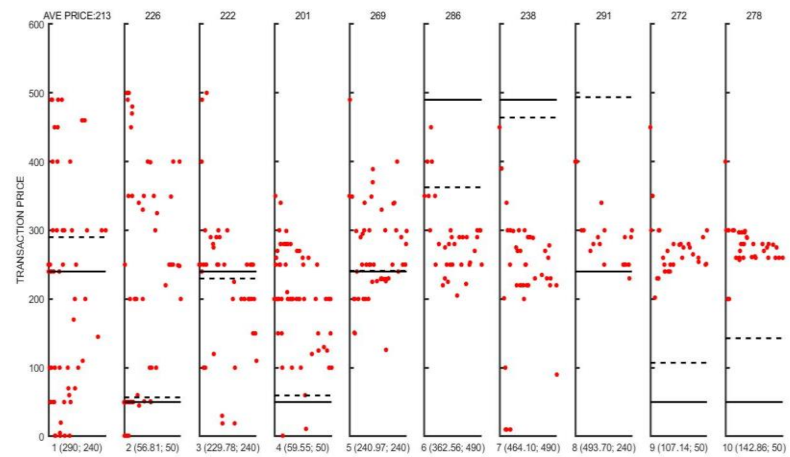

Figure IA44. *No Chat-probabilistic* Session 2.

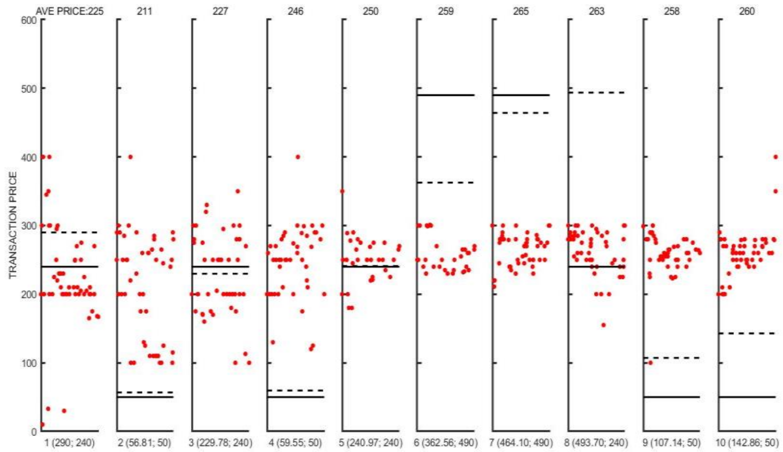

Figure IA45. *No Chat-probabilistic* Session 3.

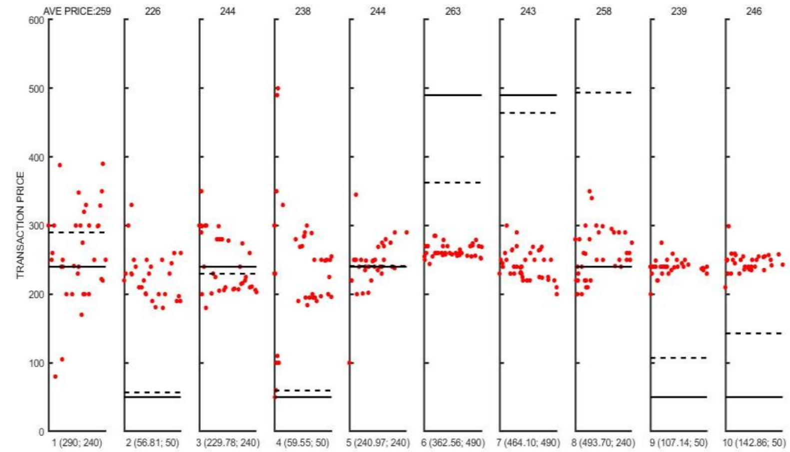

Figure IA46. *No Chat-probabilistic* Session 4.

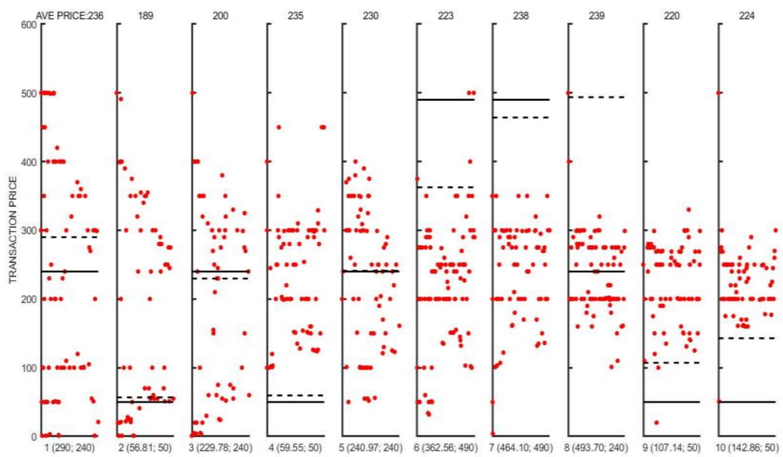

Figure IA47. *No Chat-probabilistic* Session 5.

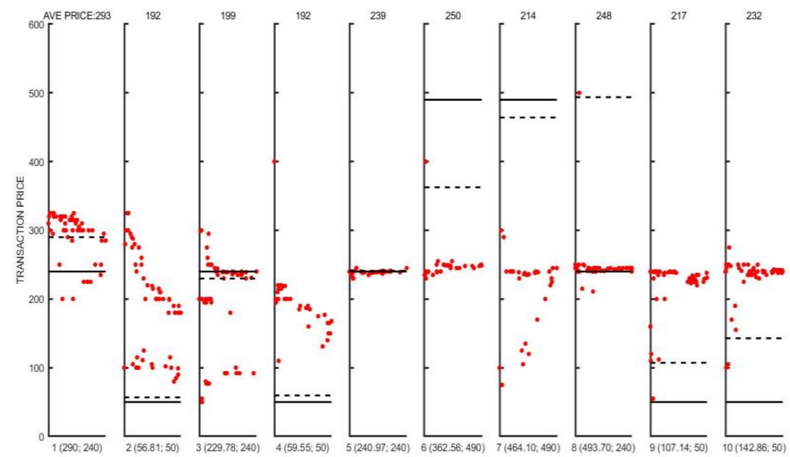

Figure IA48. *Chat-probabilistic* Session 1.

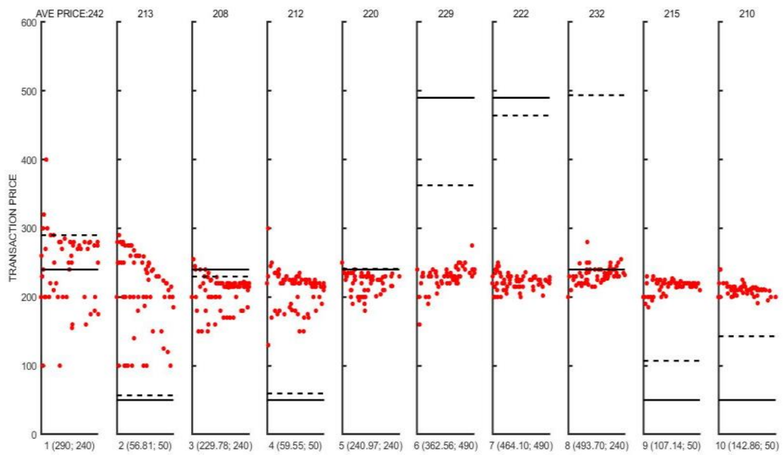

Figure IA49. *Chat-probabilistic* Session 2.

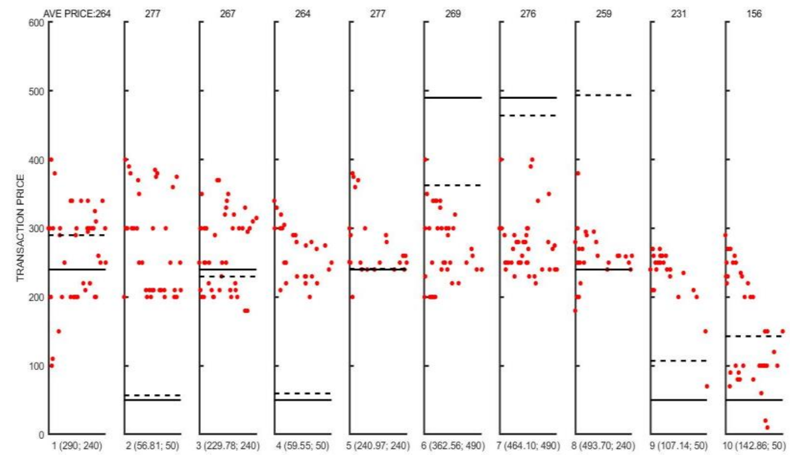

Figure IA50. *Chat-probabilistic* Session 3.

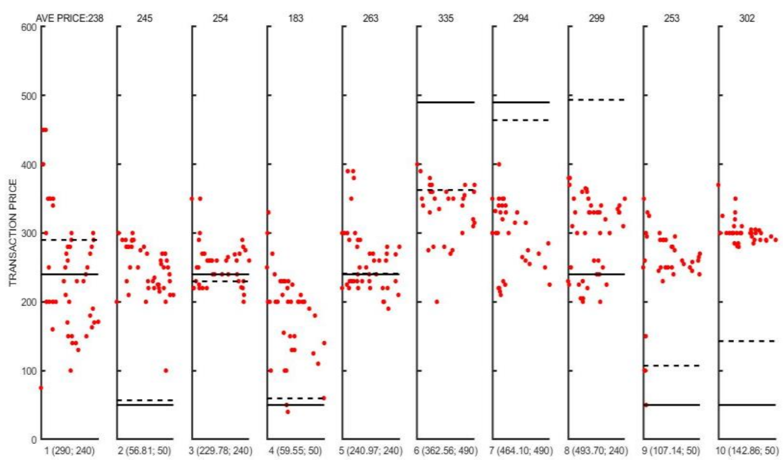

Figure IA51. *Chat-probabilistic* Session 4.

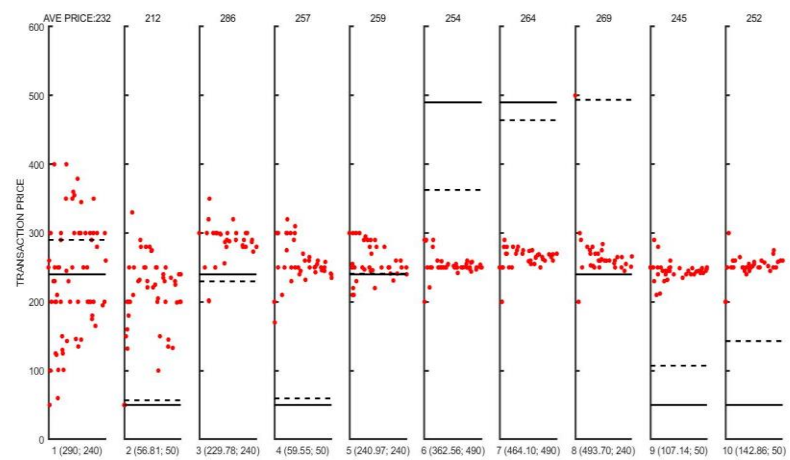

Figure IA52. *Chat-probabilistic* Session 5.

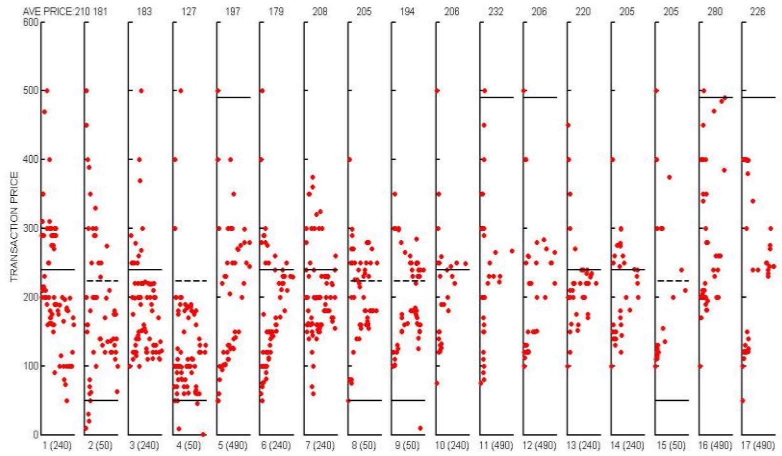

Figure IA53. *No Chat-insider* Session 1.

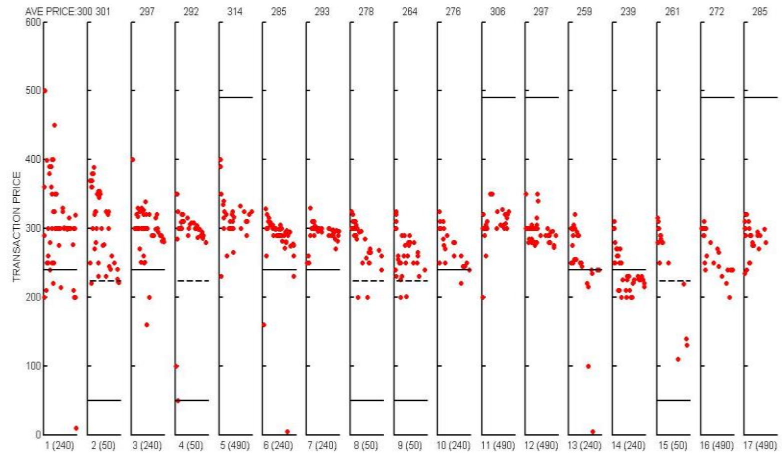

Figure IA54. *No Chat-insider* Session 2.

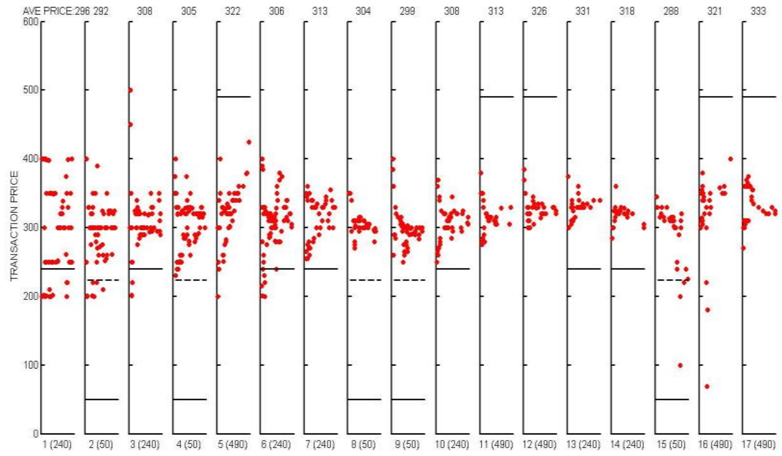

Figure IA55. *No Chat-insider* Session 3.

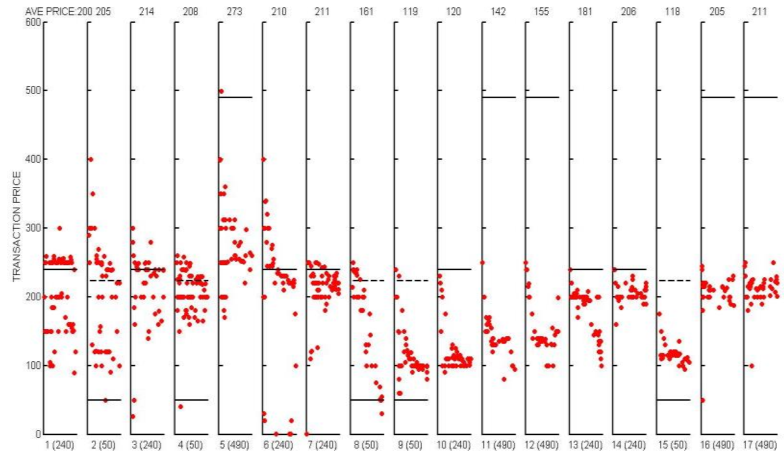

Figure IA56. *No Chat-insider* Session 4.

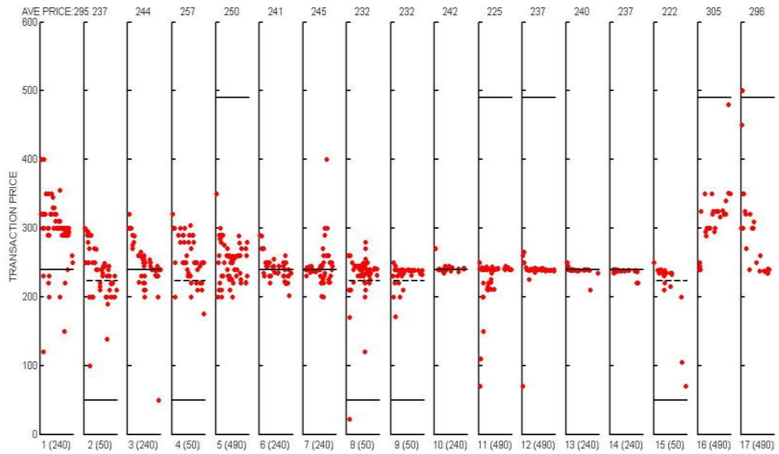

Figure IA57. *No Chat-insider* Session 5.

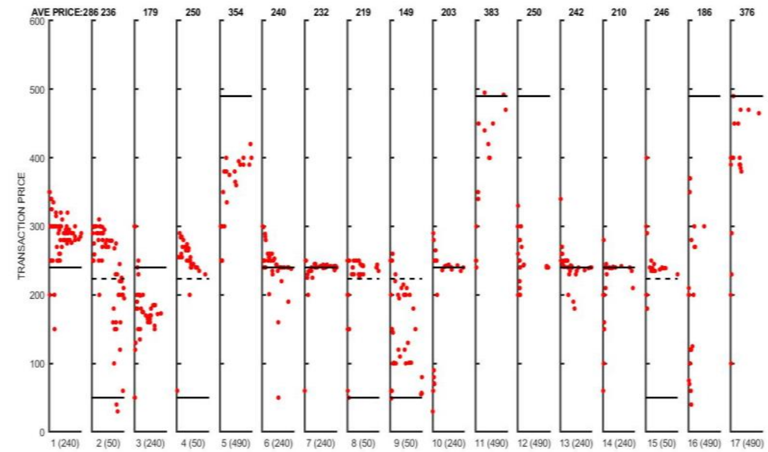

Figure IA58. *Chat-insider* Session 1.

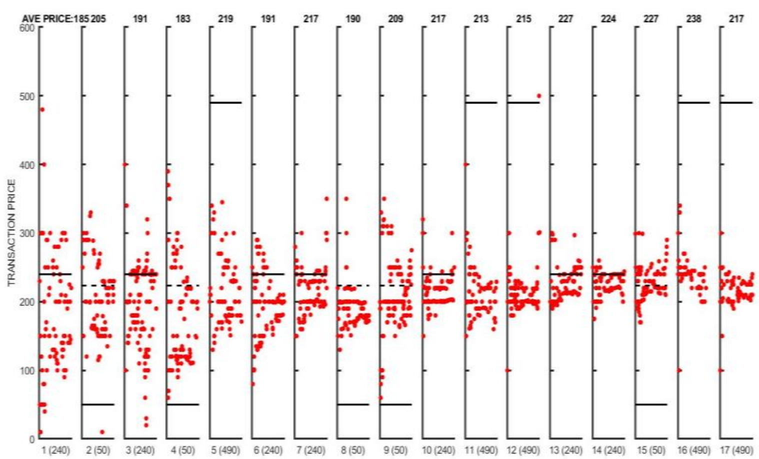

Figure IA59. *Chat-insider* Session 2.

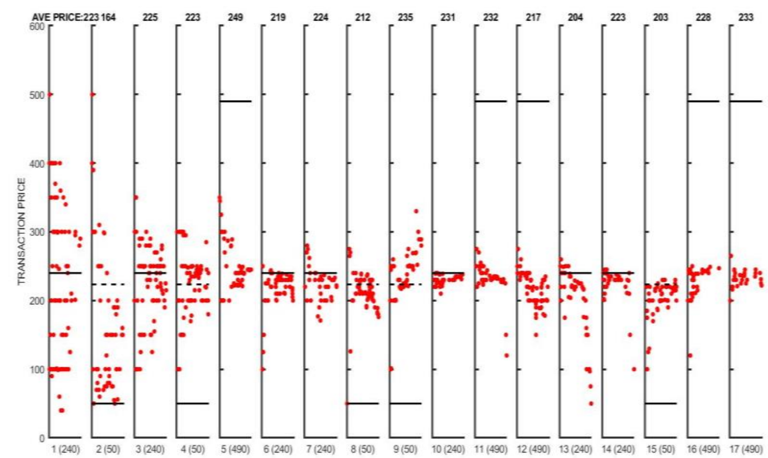

Figure IA60. *Chat-insider* Session 3.

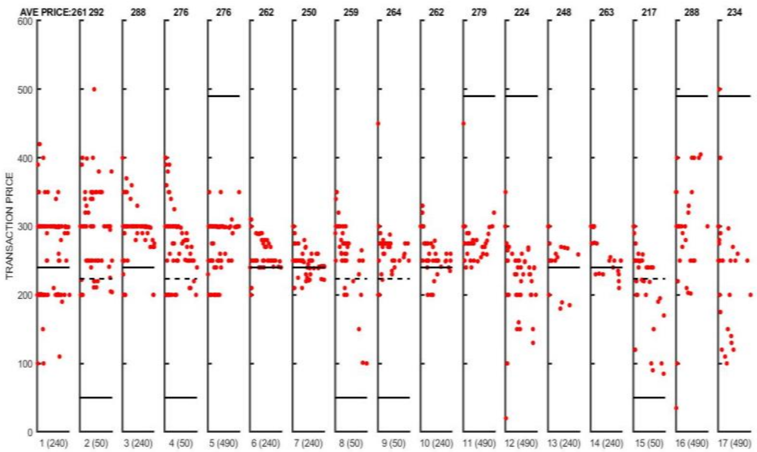

Figure IA61. *Chat-insider* Session 4.

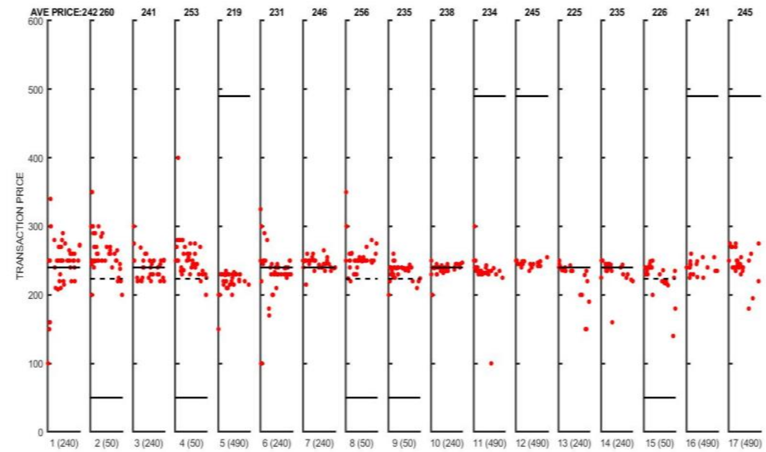

Figure IA62. *Chat-insider* Session 5.

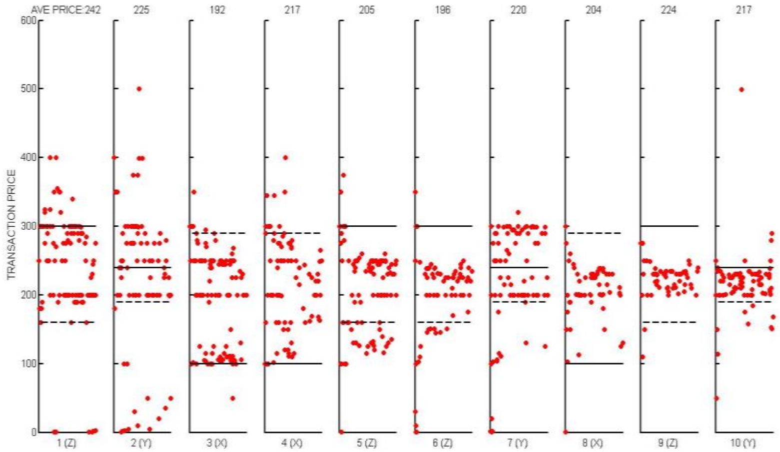

Figure IA63. *Private Value-No Chat* Session 1.

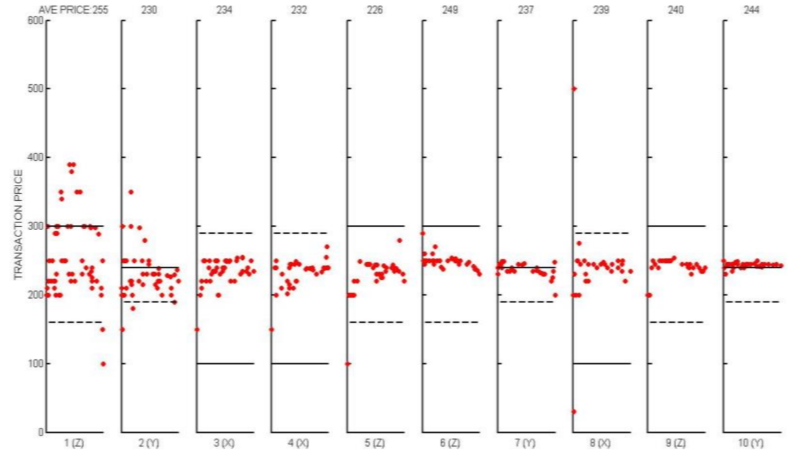

Figure IA64. *Private Value-No Chat* Session 2.

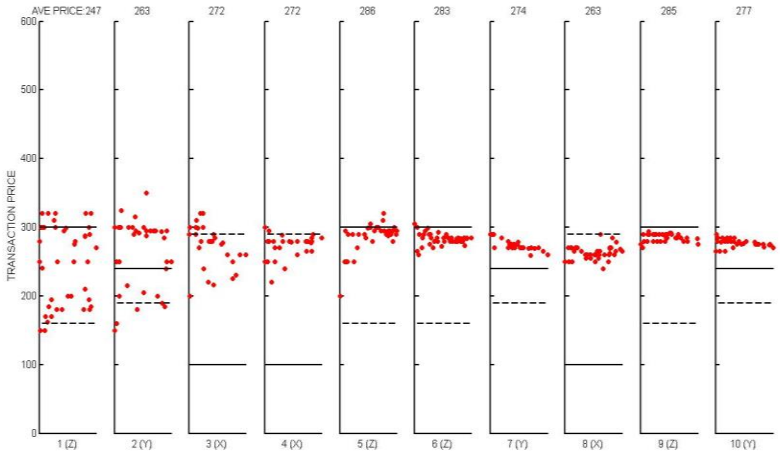

Figure IA65. *Private Value-No Chat* Session 3.

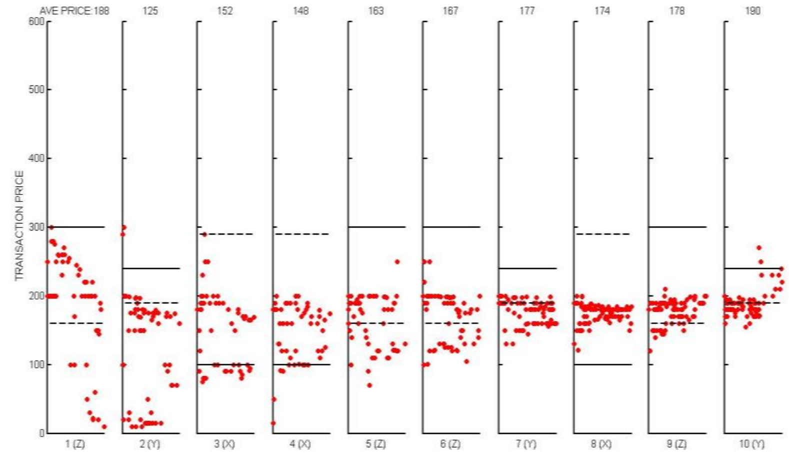

Figure IA66. *Private Value-No Chat* Session 4.

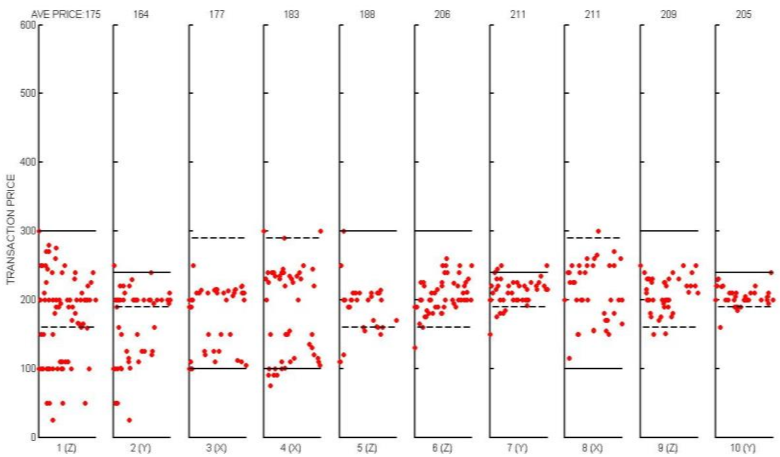

Figure IA67. *Private Value-No Chat* Session 5.

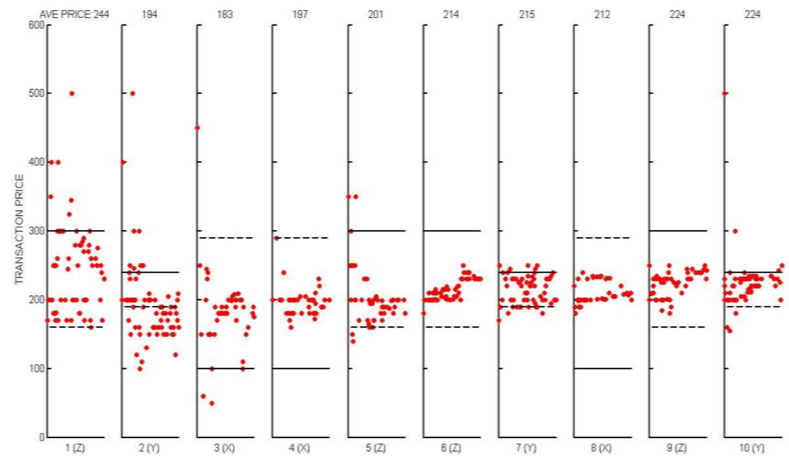

Figure IA68. *Private Value-Chat-during* Session 1.

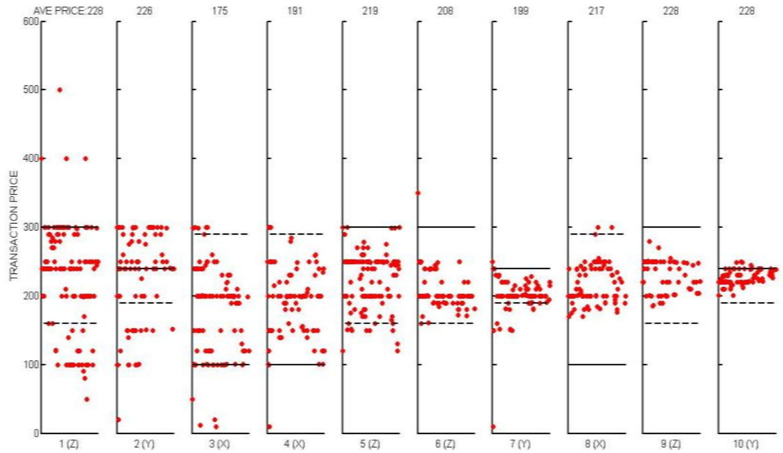

Figure IA69. *Private Value-Chat-during* Session 2.

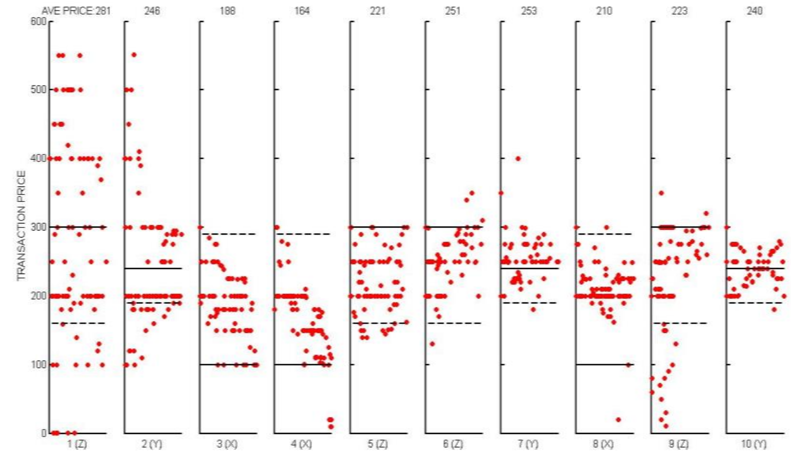

Figure IA70. *Private Value-Chat-during* Session 3.

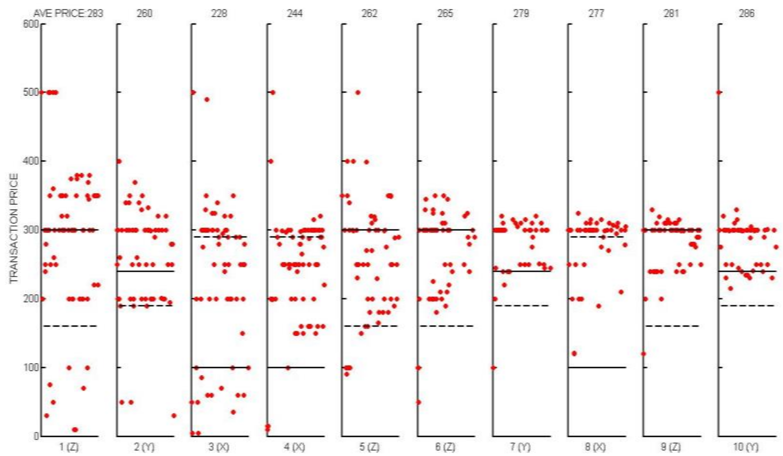

Figure IA71. *Private Value-Chat-during* Session 4.

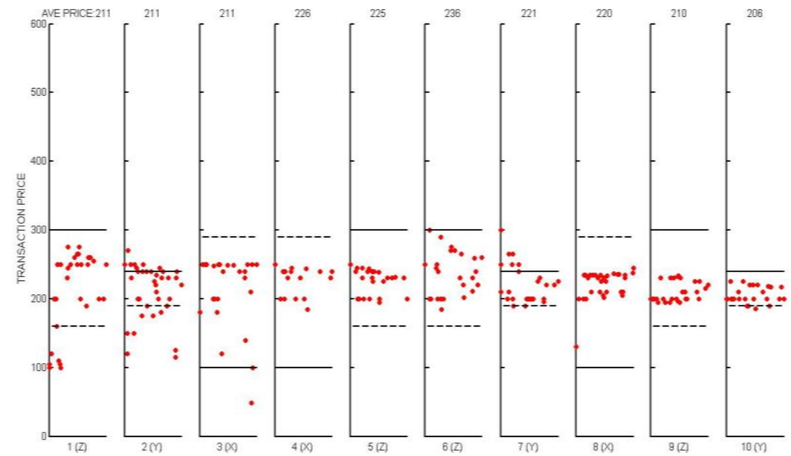

Figure IA72. *Private Value-Chat-during* Session 5.

II. Description of End-of-Experiment Survey

A. Extended Cognitive Reflection Test (CRT)

We administered the extended (seven-question) version of the CRT in which the original three questions (Frederick, 2005) are augmented with four additional questions recently developed and validated by Toplak, West, and Stanovich (2014). Our measure of cognitive reflection is given by the total number of correct answers (from 0 to 7). The Cronbach alpha reliability score for the extended CRT (0.70) is in line with that of Toplak, West, and Stanovich (2014) who reported a reliability of 0.72. Participants had 5 minutes to complete the CRT.

Taken from Frederick (2005):

(1) A bat and a ball cost $1.10 in total. The bat costs a dollar more than the ball. How much does the ball cost? ____ cents
[Correct answer: 5 cents; intuitive answer: 10 cents]

(2) If it takes 5 machines 5 minutes to make 5 widgets, how long would it take 100 machines to make 100 widgets? ____ minutes
[Correct answer: 5 minutes; intuitive answer: 100 minutes]

(3) In a lake, there is a patch of lily pads. Every day, the patch doubles in size. If it takes 48 days for the patch to cover the entire lake, how long would it take for the patch to cover half of the lake? ____ days
[Correct answer: 47 days; intuitive answer: 24 days]

Taken from Toplak et al. (2014):

(4) If John can drink one barrel of water in 6 days, and Mary can drink one barrel of water in 12 days, how long would it take them to drink one barrel of water together? _____ days
[correct answer: 4 days; intuitive answer: 9]

(5) Jerry received both the 15th highest and the 15th lowest mark in the class. How many students are in the class? ______ students
[correct answer: 29 students; intuitive answer: 30]

(6) A man buys a pig for $60, sells it for $70, buys it back for $80, and sells it finally for $90. How much has he made? _____ dollars
[correct answer: $20; intuitive answer: $10]

(7) Simon decided to invest $8,000 in the stock market one day early in 2008. Six months after he invested, on July 17, the stocks he had purchased were down 50%. Fortunately for Simon, from July 17 to October 17, the stocks he had purchased went up 75%. At this point, Simon has: a. broken even in the stock market, b. is ahead of where he began, c. has lost money
[correct answer: c; intuitive response: b]

Table IAI provides the distribution of CRT scores for our participants.

Table IAI. Distribution of CRT Scores

CRT score	% of participants
0	12.74
1	20.46
2	18.17
3	16.30
4	16.61
5	5.68
6	6.23
7	3.80
Mean	2.65
Standard Deviation	1.89

B. Theory of mind: eye gaze test (TOM)

Following Bruguier, Quartz and Bossaerts (2010) and De Martino et al. (2013), we administered the TOM test (Baron-Cohen et al. 1997) to assess participants' theory of mind skills. In this task, participants looked at images of people's eyes and had to choose one of four feelings that best described the mental state of the person whose eyes were shown. Our TOM score is defined as the number of correct answers to the 36 question, 10-minute test.

Figure IA73 is an example of one of the 36 questions in the test of Baron-Cohen et al. (1997). Table IAII provides the distribution of eye gaze test scores for our participants.

Figure IA73. Example of an eye gaze test question.

Table IAII. Distribution of Eye Gaze Test Scores

Eye Gaze Test score	0-9	10-15	16-20	21-25	26-30	>30	Mean	Standard Deviation
% of participants	1.40	0.34	5.82	26.63	53.11	12.70	26.21	4.70

C. Prosocial Index

Participants made four choices between two possible allocations of money (see Table IAIII) between themselves and another anonymous participant with whom they were randomly matched. In each session, two participants and one of the six decisions were selected at random for payment. The choice of one of the two participants in the selected decision was used to allocate payoffs between the two participants. All decisions were anonymous. The first four decisions used the same payoffs as in Bartling et al. (2009). Option A always corresponds to the egalitarian option. For each participant, we compute our prosocial index which equals the number of times a participant chose Option A in the first two decisions plus the number of times a participant chose Option B in the last two decisions.

Table IAIII. Decisions in the Social Preference Task

This table presents the decisions participants were asked to make along with the prosociality value corresponding to each decision. For each option, we display the payoff for the decision-maker and the recipient.

Decision #	Option A Self, Other	Option B Self, Other	Prosociality Value
1	\$10, \$10	\$10, \$6	1 for Option A / 0 for Option B
2	\$10, \$10	\$16, \$4	1 for Option A / 0 for Option B
3	\$10, \$10	\$10, \$18	0 for Option A / 1 for Option B
4	\$10, \$10	\$11, \$19	0 for Option A / 1 for Option B

Table IAIV. Distribution of Prosocial Index (% of participants)

Prosocial Index	All treatments	*No Chat*	*Chat*	*Chat-no reputation*	*Chat-during*	*Free-form Chat*
0	8.5	2.3	6.2	6.3	15.6	11.4
1	19.5	21.8	20.8	14.6	20.8	19.8
2	31.6	27.6	36.5	37.5	27.2	29.2
3	28.9	29.9	27.1	34.3	28.1	25.0
4	11.5	18.4	9.4	7.3	8.3	14.6
Mean	2.15	2.40	2.12	2.22	1.93	2.11
Standard Deviation	1.122	1.09	1.04	0.99	1.20	1.22

Table IAIV provides the distribution of the prosocial index scores for our participants. The prosocial index does not differ across treatments (*p*-values > 0.1 for all pairwise comparisons using a Kolmogorov-Smirnov test or WRS).

D. Honesty Index

This index was calculated using the four items of the HEXACO sincerity scale (Ashton, Lee and de Vries, 2014). We report a similar reliability coefficient as the authors (Cronbach alpha = 0.55). We report the questionnaire below:

"On the following page, you will find a series of statements about you. Please read each statement and decide how much you agree or disagree with that statement. Then indicate your response using the following scale:"

5 = strongly agree

4 = agree

3 = neutral (neither agree nor disagree)

2 = disagree

1 = strongly disagree

Please answer every statement, even if you are not completely sure of your response.

1/ If I want something from a person I dislike, I will act very nicely toward that person in order to get it.

2/ I wouldn't use flattery to get a raise or promotion at work, even if I thought it would succeed.

3/ If I want something from someone, I will laugh at that person's worst jokes.

4/ I wouldn't pretend to like someone just to get that person to do favors for me.

After reversing the scores for questions 1 and 3, the honesty index is calculated as the sum of the responses to all questions. Table IAV provides the distribution of scores for the honesty index.

Table IAV. Distribution of Honesty Index (% of participants)

Honesty Index	*Chat-no reputation*
5 or less	4.2
6	1.0
7	7.3
8	12.5
9	11.5
10	12.5
11	10.4
12	12.5
13	8.3
14	8.3
15	2.1
16 or more	9.4
Mean	10.82
Standard Deviation	3.07

III. Mean Absolute Deviation for each Session

Table IAVI reports the mean absolute deviation for each session.

Table IAVI. Mean Absolute Deviation for each Session

This table reports the mean absolute deviation (MAD) with respect to the true asset value for each session of each treatment. These values correspond to the last occurrences of each asset value, i.e., the last three market periods. The 10 private value sessions are not included.

Treatment	Session	MAD
No Chat	1	136.33
	2	122.76
	3	121.92
	4	118.37
	5	145.85
	6	150.10
	7	142.26
	8	115.93
	9	117.45
	10	141.86
Average		131.28
Chat	11	11.19
	12	11.70
	13	43.68
	14	34.96
	15	30.32
	16	22.06
	17	15.00
	18	26.41
Average		24.42
Chat-no reputation	19	133.87
	20	142.34
	21	61.41
	22	67.52
	23	144.53
	24	6.27
	25	105.82
	26	89.40
Average		93.90
Chat-during	27	94.62
	28	74.21
	29	4.18
	30	72.11
	31	86.68
	32	44.05
	33	24.86
	34	44.28
Average		55.62

Free-form Chat	35	74.41
	36	150.80
	37	83.47
	38	111.67
	39	168.58
	40	49.49
	41	0.73
	42	53.76
Average		86.62
No Chat-probabilistic	43	163.43
	44	203.01
	45	155.52
	46	160.89
	47	154.18
Average		167.41
Chat-probabilistic	48	147.75
	49	149.49
	50	131.24
	51	161.47
	52	156.59
Average		149.31
No Chat-insider	53	164.34
	54	121.94
	55	162.69
	56	136.74
	57	123.59
Average		141.86
Chat-insider	58	108.03
	59	158.56
	60	139.57
	61	157.39
	62	145.10
Average		141.73

IV. Experiment Instructions

The instructions for each experimental treatment are included in this section of the Internet Appendix (see link **https://bit.ly/2UxI8xi**).