Information, Asset Price Volatility, and Liquidity *

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Abstract

How are asset price volatility and liquidity impacted by public perception of the economic state and by market competitivity? We wish to understand the direct impacts as well as indirect impacts via information acquisition and aggregation. To investigate, we design a laboratory experiment with human subjects as bond investors, and exogenously vary the bond default rate, the private information cost schedule, and the market format. To discipline the experiment parameters and to obtain hypotheses for empirical testing, we construct a theoretical model that closely parallels the experiment. We find that the laboratory data support most theoretical predictions, e.g., liquidity increases when traders purchase more precise private information, when public information indicates a less ominous state, and when the market is less competitive. Overall price volatility also increases with more precise private information and less competitivity, but it decreases with less ominous public information. Decomposing volatility into "efficient" and "inefficient" components may offer insight for policy analysis.

Keywords: volatility; liquidity; experiment; BDM; Continuous Double Auction.
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1 Introduction

Economic and financial crises are often accompanied by illiquidity and asset price volatility. The underlying mechanisms are unclear, and are difficult to identify in existing field data because crises are rare and idiosyncratic and also because relevant variables are difficult to measure. Among numerous possible mechanisms, we investigate those mediated by private information acquisition, using a theory-guided laboratory experiment. More specifically, our main concerns are how price volatility and liquidity can be affected by public perception of the economic state (crisis vs non-crisis) and by market competitivity. We wish to understand direct impacts, and also indirect impacts via information acquisition and aggregation.

With those empirical concerns in mind, and given the intrinsic limitations of field data, we turn to laboratory experiments. To discipline the parameter values used in the experiments, and to obtain clear hypotheses to guide data analysis, we begin by constructing a tractable theoretical model. The model has a stylized bond market in which key variables — public information about the economic state, information costs, and market competitivity — are varied exogenously.

The model predicts that risk-neutral traders with rational expectations will acquire more private information (and so the market will have more aggregated information) when information cost is lower and when public information indicates a more ominous economic state (i.e., the bond's default risk is higher, interpreted as a looming "crisis"). The model also predicts that the more competitive market formats (the Call Market and the Continuous Double Auction) generate more polarized (i.e., more asymmetric) information acquisition choices among traders. Furthermore, the model predicts that more ominous public information itself will increase volatility and decrease liquidity, while more precise private information (arising endogenously from more ominous public information) will increase liquidity and further increase overall price volatility.

Our laboratory environment closely parallels the theoretical model. Treatment variables include information cost, public information about the economic state, and market competitivity. Laboratory procedures enable precise observation of endogenous private information acquisition and market outcomes. More specifically, human subject traders receive free public information on the bond's default probability. The traders then can purchase costly private information about the "haircut," or recovery rate $m \in [0, 1]$ in case of default. In particular, given a cost schedule that is based on Shannon entropy, traders choose how much to pay to narrow down the range of m. After that, they trade bonds in a laboratory market using either the classic Becker-DeGroot-Marschak (BDM), the Call Market (CM), or the Continuous Double Auction (CDA) format. Varying the market format from BDM to CM to CDA increases the degree of market competitivity. We observe each subject's endogenous purchase of private information as well as all subsequent bond trades and prices, and directly measure aggregated information, asset price volatility, and liquidity.

The laboratory data support most of the hypotheses arising from our theoretical framework. We find that our laboratory markets generate reasonable results regarding information acquisition and aggregation and that the markets tend to be quite efficient. Consistent with theory, private information acquisition increases with more ominous public information (i.e., higher default probability), decreases with acquisition costs, and polarizes with greater market competitivity. Given these basic findings, we turn to our main questions and find, e.g., that price volatility and liquidity increase with private information acquisition (and aggregation) and decrease with market competitivity, while information cost has no direct impact. Ominous public information has opposite effects on price volatility and liquidity: it increases the former but decreases the latter. A practical interpretation is that, when perceived default risk is elevated (e.g., during an actual crisis), investors will react by acquiring more private information, and that can further elevate overall asset price volatility but may improve liquidity. Hence, once endogenous information acquisition is taken into account, there is a tradeoff between volatility and illiquidity that should be of interest to policymakers.

Our paper contributes to the general theoretical and empirical understanding of how information impacts asset price volatility and liquidity. We make two specific contributions. First, to our knowledge ours is the first paper to combine theory and laboratory experiments to study how private information acquisition and market information aggregation affect liquidity and asset price volatility. In particular, we were unable to find an off-the-shelf model of a bond market implementable in the laboratory that could generate testable predictions about information acquisition as well as price volatility, and liquidity. Our model delivers exact algebraic expressions for the least competitive market format and delivers numerical approximations for the more competitive formats. Future researchers may be able to glean useful elements from our theoretical model.

Empirical studies with field data are difficult because relevant variables there (e.g., private information acquisition and shocks to fundamentals) are either unobservable or difficult to disentangle from each other. By contrast, our laboratory experiment permits precise observation of each information source (i.e., public, private, or market aggregates) and shocks, while the theoretical framework provides clear predictions. Our setup also allows us to distinguish the "efficient" volatility that arises from closely tracking fundamental value (which varies with default risk) from the "inefficient" volatility arising from mispricing, and to examine how each of them is affected by both public and private information.[1]

A second specific contribution is to laboratory studies comparing market formats. As noted in the literature survey below, such comparisons are not uncommon for goods markets and have been made in a few specialized asset market contexts. To our knowledge, we are the first to examine the impact of market competitivity on asset price volatility and liquidity as well as on information acquisition and aggregation. Market competitivity is interesting in its own right and is also crucial for our study because it governs the information aggregation process and so may have a major impact on market outcomes such as volatility and liquidity.

Our theoretical model correctly predicts polarized information acquisition choices in more competitive markets, but has no clear prediction on how competitivity affects market performance. On the one hand, greater competitivity can increase interactions and promote better aggregation

[1]We refer to volatility as efficient or inefficient not from the perspective of welfare, but rather in terms of asset price efficiency.

of acquired information and thus increase volatility and liquidity. On the other hand, precisely because greater competitivity improves the dissemination of private information in the market, it reduces the individual incentive to acquire private information, and thus tends to reduce aggregate information, volatility, and liquidity. Hence, it becomes an empirical question to determine the net impact of competitivity. This empirical question is difficult to answer using field data due to incomparability across existing financial market formats. Our laboratory experiment makes direct comparisons possible.

Our experiment considers three market formats that offer different levels of competitivity, i.e., different degrees of opportunity for each trader to outbid others. Our least competitive market format is a variant of the classic Becker-DeGroot-Marschak (BDM) procedure. Our BDM format provides a baseline of individual choice in which the market does not aggregate other traders' private information. It can be considered an extreme counterpart of OTC bond markets where competitivity is low and little of investors' private information is revealed. Our second market format is the Call Market (CM), which is more competitive than BDM. Unlike the BDM, the CM determines the bond price endogenously and thus its price should reflect both public and private information. Lastly, our most competitive format is the Continuous Double Auction (CDA), featured in most major financial markets. Our CDA enables traders to learn within each round about others' private information by observing their live bids, asks, and transactions, which may improve information aggregation relative to the CM and alter traders' incentives to acquire private information in the first place. Varying the market format from BDM to CM to CDA market provides a robustness check and enables us to disentangle the impact of individual behavioral idiosyncrasies from the impact of market interactions, e.g., on information aggregation and liquidity.

Literature. Two strands of literature are closely related to our work. The first strand uses theory and/or field data to study the impact of costly information acquisition on financial markets. For instance, Gu and Stangebye [2023] establish a general equilibrium model with quantitative results that are derived from calibrated parameters reflecting the data of sovereign default episodes and information acquisition. Like us, they predict that price volatility increases with private information during crisis periods and decreases during normal times. Our current paper, however, derives a priori predictions in a partial equilibrium framework, and tests them with laboratory data. Our experiment design and data enable a deeper analysis by focusing on market competitivity and implications of costly information acquisition for liquidity and for price volatility and its decomposition into "efficient" and "inefficient" elements.

Many other papers have explored the implications of costly information acquisition in a theoretical setting. For instance, Angeletos and Werning [2006] and Carlson and Hale [2006] explore how market-based information acquisition or rating agencies affect equilibrium multiplicity or uniqueness in variations on the canonical model of Morris and Shin [1998]. More recently, Cole et al. [2022] also study a model of costly information acquisition in sovereign debt markets, but their focus is on the potential of this information channel to cause contagion effects across regions. Pagano and

Volpin [2012] show the impact of information transparency on welfare changes that are related to market liquidity. Bassetto and Galli [2019] study the role of information on sovereign bond pricing in a two-period Bayesian trading game, focusing on implications for inflation risk.

Empirically, Foley-Fisher et al. [2020] examine the impact of state-contingent information acquisition on the liquidity (measured by bid-ask spreads) of collateralized loan obligations using field data. The authors emphasize the role of ex-ante asymmetric information and adverse selection; only experts acquire information in the bad-news (e.g., Covid pandemic) state. In contrast, our model and empirical analysis using the laboratory data allow bid-ask spreads to respond to players' information acquisition, creating *ex-post* information asymmetries and adverse selection, and also allow *direct* response of spreads to the state indicated by public information. Of course, our laboratory experiment also features tighter control than the natural experiment in Foley-Fisher et al. [2020], e.g., our players all have the same initial endowment and face the same private information cost schedule, and both are known to (and controlled by) the researchers. In addition, Barber and Odean [2008], Da et al. [2011], Ben-Rephael et al. [2017] show empirically that investor information acquisition/attention predicts stock returns and Cziraki et al. [2021] find that the geographic distribution of attention matters for stock returns. Vlastakis and Markellos [2012], Andrei and Hasler [2015], and Dimpfl and Jank [2016] also show that an increase in investor attention corresponds to an increase in stock-return volatility.

Costly information acquisition in *laboratory* asset markets (e.g., Sunder [1992]) is the second closely related strand of literature. Most recent examples, e.g., Huber et al. [2011] and Asparouhova et al. [2017], do not focus, as we do, on the role of public information nor on asset price volatility and liquidity. A partial exception, Halim et al. [2019], considers as we do information acquired from public signals and market prices as well as private purchase. However, their focus is on social networks. We eliminate complicated network effects to focus more sharply on how the other information channels affect asset price volatility and liquidity.

There is also a growing experimental literature on interactions between costly private information and public information in financial markets. In most of this literature, the two types of information are substitutes. For instance, Ruiz-Buforn et al. [2021] study private information acquisition after introducing a public signal. They find that the latter crowds out the former and reduces the efficiency of prices in incorporating and transmitting the information. In our setting, private information is not a substitute for public information. Instead, the value of private information is contingent on the content of public information, e.g., more ominous public information (default more likely) enhances the value of private information (on the recovery rate m).

Other strands of literature also have some relevance to our project. For instance, there is a tradition of comparing market formats in the laboratory, especially variants of CM and CDA, beginning with Plott and Smith [1978]. Most such studies focus on comparing allocational efficiency in goods markets. Of those that consider asset markets, most focus on multi-period assets with declining fundamental values, which are prone to price bubbles, as first introduced by Smith et al. [1988]. More recent examples include Van Boening et al. [1993], Lugovskyy et al. [2014], Deck et al.

[2020], and Guler et al. [2021]; for a survey, see Biais et al. [2005].

Several laboratory studies compare the impact of *exogenous* private information across different asset market formats. Friedman [1993] finds that the Call Market format (there referred to as the "clearinghouse institution") aggregates private information virtually as well as does the Continuous Double Auction, and Theissen [2000] confirms that result. Schnitzlein [1996] and Kuo and Li [2011] both explore the impact of trading formats on market quality, with the former finding lower adverse selection costs in Call Markets and the latter noting smaller quoted spreads and price volatility in Continuous Double Auctions. Ngangoué and Weizsäcker [2021] find that subjects respond much better to asset prices that incorporate other traders' private information when the process is sequential (as in a CDA) than when the process is simultaneous and contingent reasoning is required (as in a CM).

There is also an extensive literature on the BDM procedure, invented to induce truth-telling by Becker et al. [1964]. Reports of apparent departures from truth-telling in empirical practice go back to Lichtenstein and Slovic [1971]; see Cason and Plott [2014] for a recent dissection of empirical issues with BDM in its original context. Recently, Halevy et al. [2023] study a variant of BDM using an interface similar to ours to elicit analogues of bid and ask prices. Classic choice models predict that the two elicitations will coincide, but they find gaps that seem inconsistent with even extremely general choice theories.

Our paper proceeds as follows. In Section 2 we establish a theoretical framework to guide the parameterization of experiments and to generate testable predictions. That section also details the three market formats. Section 3 lays out the experiment design and briefly discusses the laboratory data. Section 4 presents hypotheses, empirical specifications, and the main inferences drawn from our data. Section 5 discusses our findings and offers concluding remarks. Online Appendix A includes mathematical details for the theoretical framework. Appendix B, also online, discusses the laboratory data more in detail and validates the data by examining information acquisition and aggregation in the experiments. Online Appendix C collects supplementary data analysis. The last online Appendix is a copy of instructions to laboratory subjects.

2 Theoretical Model

We now construct a framework that is tractable enough to produce clear theoretical predictions for the variables of interest and that is also implementable in the laboratory while providing guidance for the experiment's exogenous parameters.

2.1 Set Up

Consider a bond with indivisible units that each pay a single state-dependent liquidating dividend M. With probability $g \in [0, 1]$, the state is *default* and M is an amount $m \in (0, 1)$ known as the *recovery rate*. Otherwise, the state is *no-default*, and the liquidating dividend is $M = 1$. The value of g is public knowledge. Traders also know the distribution of the recovery rate m but not the realization. In our model and experiment, the recovery rate upon default has the uniform distribution, $m \sim U[0,1]$.[2] The uniform distribution is easier for our human subjects to understand, although it does not necessarily make solving the model easier. For simplicity and clarity, we assume that traders are risk neutral.[3]

The event timeline is as follows. Each trader is endowed initially with a single unit of the bond, and the default probability g is publicly announced. Each trader then has the opportunity to purchase private information width $w \in (0,1]$ at a specified cost $C(k,w) \geq 0$; the cost parameter $k > 0$ is explained below. Then she receives a private signal $[m_L, m_L + w] \subset [0,1]$ where, as detailed below, m_L is the lower endpoint of an interval of chosen width w within which the true recovery rate m lies. As detailed below, a market for the asset then opens and each trader can sell or purchase a single bond. Finally, the true state is revealed and each trader receives payoff

$$\Pi = W - C(k,w) - \eta + r + hM, \tag{1}$$

where W is exogenous initial wealth, $C(k,w)$ is expenditure on private information, η is expenditure on bond if she purchased one, r is revenue received if she sold a bond, $h \in \{0,1,2\}$ is the post-trade set of possible bond holdings, and $M \in \{1,m\}$ is again the bond's realized liquidating dividend.

The cost of purchasing an interval for m of width $w \in (0,1)$ in our model is proportional to the informativeness of the interval, where informativeness I is the difference between Shannon entropy before and after conditioning m on the revealed interval $[m_L, m_L + w]$. Given uniform distributions, $I = E[\ln(p(m|m_L,w))] - E[\ln(p(m))] = \ln(1/w) - \ln 1 = -\ln w$, where $p(m)$ is m's unconditional probability distribution and $p(m|m_L,w)$ is the conditional probability distribution of m after choosing w and observing m_L.[4] For the specified cost parameter $k > 0$, the information cost is therefore $C(k,w) = kI = -k\ln w > 0$.

Note that wider intervals (larger w) give less precise information and cost less than narrower intervals. At cost 0, a trader can choose $w = 1$, i.e., no private information is purchased, in which case she knows only the prior distribution of m. If a trader chooses $w < 1$ then she sees an interval $[m_L, m_U]$ determined as follows. Given an independent draw of $\rho \sim U[0,1]$, set $m_L = m - \rho w$, truncated below at 0 and above at $1 - w$, and set $m_U = m_L + w$. Thus, $[m_L, m_U]$ is a random sub-interval of $[0,1]$ of width w that contains the true value of m. It is easy to see that the Bayesian posterior density of m is uniform over the realized interval in the untruncated case ($m - \rho w >$

[2] Many previous studies take state variables to be discrete or even binary, but (given our emphasis on the acquisition of private information with entropy-based cost) we find it useful to make the recovery rate m continuous. In addition, previous research has also shown a wide range of recovery rates for (sovereign) bonds (Asonuma et al. [2023], Jankowitsch et al. [2014]).

[3] We acknowledge that risk aversion may help explain financial market data, but here risk neutrality seems roughly consistent with our laboratory experiment in that (i) ex-ante, traders face small stakes each period, and (ii) ex-post, the estimated risk premium is relatively small.

[4] As detailed in Lemma 1 in Appendix A.1, in some cases, m_L is truncated and then the conditional distribution is triangular instead of uniform. Here we use entropy only to establish a cost function for purchasing private information, and for that purpose, we need only consider uniform distributions.

$0, m + (1-\rho)w < 1$), and therefore has expected value $m_L + \frac{w}{2}$. As for the truncated cases, we show in Lemma 1 in Appendix A.1 that the densities are triangular and that the cdf for m_L has a mass of $\frac{w}{2}$ at its minimum value 0 and at its maximum value $1-w$, but in between it is uniform of density 1.

2.2 BDM Format and Optimal Choice

We now consider three market formats of differing competitivity, and for each find optimal (or equilibrium) behavior, and thus obtain predictions testable in the laboratory. The first market format is a variant of the classic Becker-DeGroot-Marschak (BDM) procedure. In our BDM format, each trader independently trades with a single automated agent as follows. Each round, the trader posts a single bid price b and a single ask price a, subject to the constraints $0 \leq b \leq a \leq 1$. Then the automated agent draws a random price $q \sim U[0,1]$.

- If $q \leq b$, then the trader purchases a single unit at price q, so $\eta = q, r = 0, h = 2$ in eq. (1).
- If $q \in (b, a)$, then there is no trade, so $\eta = 0, r = 0$ and $h = 1$.
- If $q \geq a$, then the trader sells a single unit of bond at price q, so $\eta = 0, r = q$ and $h = 0$.

The BDM procedure incentivizes truthtelling, that is, for each trader to report her true willingness-to-pay for the bond, $\hat{V}$, i.e., to set $b = a = \hat{V}$.[5] If she is Bayesian rational then $\hat{V} = E(M|m_L, w) = 1 - g + g\hat{m}$, where M is bond's liquidating dividend and $\hat{m}$ is her posterior expectation of the recovery rate given her chosen w and observed m_L, as per Lemma 1.3 in Appendix A.1.

A rational risk-neutral trader will choose $w \in (0,1]$ so as to maximize the expected payoff from equation (1). Writing the expectation of net benefit $-\eta + r + hM$ as $B(g,w)$, the problem is

$$\begin{aligned}\max_w \Pi &= W - C(k,w) + B(g,w) \\ &= W + k \ln w + \int_0^{1-w} \int_0^1 \left\{ \int_0^{\hat{V}} [2(1-g+gm) - q] f(q) dq \right. \\ &\qquad \left. + \int_{\hat{V}}^1 q f(q) dq \right\} f(m|m_L) f(m_L) dm dm_L, \qquad (2)\end{aligned}$$

where W is the initial wealth parameter including sunk cost (e.g., participation fees in the experiment), and $C(k,w) = -k \ln w$ is the entropy cost of chosen information precision (i.e., of interval width w). To compute the expected net benefit $B(g,w)$ of w given default probability g, recall that the BDM truthtelling strategy $b = a = \hat{V}$ is optimal. Then $B(g,w)$ can be written as a triple integral, since the expectation must be taken with respect to the distributions of (a) the market

[5] To see this, consider the following variant on a standard argument. Suppose that a trader sets $b < \hat{V}$. If $q \leq b$ or $q \geq \hat{V}$, then the outcome is the same as if she had chosen $b = \hat{V}$. However, if it turns out that $q \in (b, \hat{V})$ then she would miss a buying opportunity that she regards as beneficial. If she instead chose to submit a bid $b > \hat{V}$ and it turns out that $q \in (b, \hat{V})$, then she would buy at a price that she regards as not beneficial. Likewise, any deviation of her chosen ask a from $\hat{V}$ either will have no impact or else will lead to a missed beneficial sale of a bond or to a non-beneficial sale.

price q, (b) the realized recovery rate m conditioned on the chosen w and the to-be-observed m_L, and (c) the realization of m_L given chosen w. The first integrand, $[2(1-g+gm)-q]$, represents the net value of the two bonds the trader holds if she purchases one at price $q < \hat{V}$. The second integrand, q, represents her receipts if she sells her endowed bond (when $q > \hat{V}$). Densities for all relevant variables are denoted $f(\cdot)$.

In Appendix A.2, we solve problem (2) and prove the following:[6]

Proposition 1. *A risk-neutral trader facing the BDM procedure with default rate $g \in (0,1)$ and entropy cost parameter $k > 0$ will optimally choose*

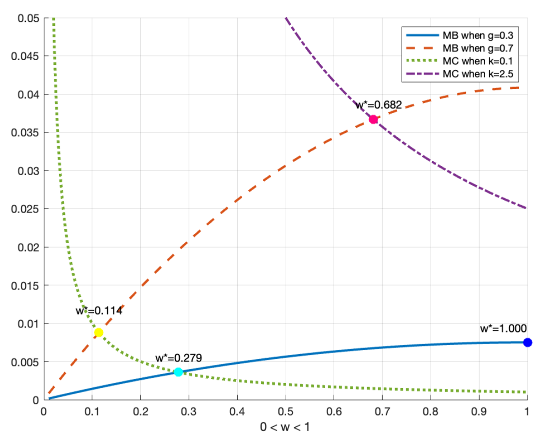
(i) the unique width $w^* \in (0,1)$ that solves the cubic equation $w^2(2-w) = \frac{12k}{g^2}$ if $12k < g^2$, and otherwise will choose $w^* = 1$.

(ii) $\frac{\partial w^*}{\partial k} > 0$ for $0 < w^* \leq 1$ and $0 \leq k \leq \frac{g^2}{12}$.

(iii) $\frac{\partial w^*}{\partial g} < 0$ for $0 < w^* \leq 1$ and $0 \leq g \leq \sqrt{12k}$.

(iv) Given the chosen w^* and subsequently revealed m_L, the trader will optimally choose bid and ask prices $b = a = \hat{V} \equiv E(M|m_L, w) = 1 - g + g\hat{m}$, for $\hat{m} \equiv E(m|m_L, w)$ as in Lemma 1.

Figure 1: Marginal Benefits and Costs



The key insight in the proof is that the first order condition $-\frac{\partial}{\partial w}C(k,w) = -\frac{\partial}{\partial w}B(g,w)$ for equation (2) reduces to

$$\frac{k}{w} = \frac{1}{12}g^2 w(2-w). \tag{3}$$

The cubic equation in Proposition 1(i) is a slight rearrangement of (3), which is graphed in Figure 1. Note that costs and benefits of increasing private information precision are from *decreasing* width w, so the slopes as drawn are the reverse of usual. The marginal cost (MC) curve for $k = 0.1$ intersects the marginal benefit curve for $g = 0.3$ at $w^* \approx 0.3$, and intersects the marginal benefit

[6] In this paper, we use signs of partial derivative expressions to indicate comparative statics directions for variables like k, g, and later for N and competitivity. Our intention is to make text and tables easy to read, and not to claim that the relevant functions are differentiable nor (in the case of N and competitivity) even continuous.

(MB) curve for $g = 0.7$ at $w^* \approx 0.1$. For the same k, optimal private information precision increases (w^* shrinks) as g increases (more ominous public information). When $k = 2.5$, the marginal cost curve shifts out, resulting in a corner solution at $w^* = 1$ when $g = 0.3$, while $w^* \approx 0.7$ when $g = 0.7$. That is, when information cost k rises, optimal private information precision decreases (w^* gets wider). We use these four (k, g) value combinations in the experiment because, as Figure 1 shows, they provide a nice separation of the optimal width choices.

2.3 Competitive Markets

Having established a minimally competitive benchmark using BDM, we now consider how market competition and endogenous pricing will influence information acquisition decisions, and the subsequent market-wide impact on information aggregation, price volatility, and liquidity.

2.3.1 Trader's Problem

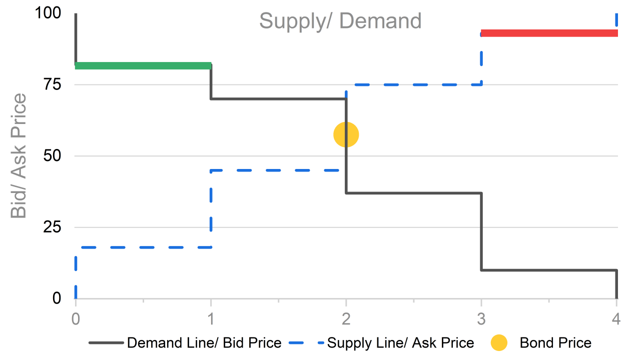
We first describe the two competitive market formats that we use in the experiment—the Call Market (CM) and the Continuous Double Auction (CDA)—and show how they alter the trader's optimization problem.

Call Market. Variants of CM are widely used by economic theorists, and some major financial markets use a CM to determine initial prices when the market opens. Our CM algorithm follows.

- Traders $i = 1, ..., N$ simultaneously each post a single bid price b_i and a single ask price $a_i \geq b_i \geq 0$.
- The algorithm computes the clearing price $q =$ median of all bids and asks $\{a_1, b_1, ..., a_N, b_N\}$.
- Trader i sells her endowed single bond at price q if $a_i < q$ and buys a single bond at price q if $b_i > q$.
- If any bids or asks coincide exactly with q, then as many as possible are cleared at that price: the light side (e.g., supply if there are more remaining bids than asks tied at price q) is fully cleared, and the other (heavy) side is rationed randomly.

An equivalent description (which generalizes to cases with unequal numbers of bids and asks, but requires more elaborate notation to formalize) is that the CM determines the bond price endogenously via the demand and supply embodied in all traders' bids and asks. More specifically, the CM algorithm sorts bids from highest to lowest to form the Demand curve, and sorts asks from lowest to highest to form a Supply curve. The bond price q (yellow dot in Figure 2) is the price (or the midpoint of the price segment) where Supply (blue dashed line) and Demand (black solid line) coincide. Figure 2 provides an illustration of a Call Market with four traders, where each step is a bid/ask by a trader. For example, the thick green and red lines are one trader's bid and ask, respectively. The step-wise demand and supply can more closely approximate smooth curves when there are more traders in the Call Market.

Figure 2: Bond Price in Call Market



Notes: The solid black line is demand function and the dashed blue line is supply function; a particular trader's bid and ask are marked green and red, respectively. The height of the yellow dot is the market clearing price q.

The trader's optimization problem here resembles that of a trader in a BDM market, as what matters is the payoff expectation over q, over m conditioned on the signal m_L, and over the possible signals m_L given the chosen w. But there are two major differences. First, the Call Market price q is not uniformly distributed. We will write its density as $f(q)$ and defer further discussion until Section 2.3.2. Second, as we will also see in Section 2.3.2, the trader will optimally offset her bid and ask prices away from $\hat{V}$ by choosing some half-spread $s > 0$. Thus, as well as purchasing a bond when $q \leq b = \hat{V} - s$ and selling a bond when $q \geq a = \hat{V} + s$, there is also a no-action scenario when $b < q < a$. In that scenario she neither buys nor sells a bond so her payoff is the expected value $V(m) = 1 - g + gm$ of her single endowed bond. Consequently, the Call Market trader's optimization problem can be expressed as:

$$\max_{w,s\in[0,1]} \quad \Pi = W - C(k,w) + \int_0^{1-w}\int_0^1 \left\{ \int_0^{\hat{V}-s} [2(1-g+gm) - q] f(q)dq \right.$$
$$\left. + \int_{\hat{V}-s}^{\hat{V}+s} (1-g+gm) f(q)dq + \int_{\hat{V}+s}^{1} q f(q)dq \right\} f(m|m_L) f(m_L) dm dm_L, \qquad (4)$$

where $\hat{V} = 1 - g + g\hat{m}$, $\hat{m} = E(m|m_L, w)$, and $f(\cdot)$ is the density for each of the relevant variable.

Continuous Double Auction. The third format we consider, the Continuous Double Auction (CDA), allows traders to continually place and adjust their bids and asks each round, and to transact in real-time at any instant during a trading round.

It is our most competitive format in that every trader at every moment has the opportunity to outbid rival traders, i.e., to offer more attractive bids or asks. For the last century or more, most major financial asset markets around the world have used some variant of the CDA. Numerous laboratory studies beginning with Smith [1962] show that simple CDA markets are exceptionally efficient. Our CDA market algorithm proceeds as follows.

- Traders $i = 1, ..., N$ freely post and adjust bid prices b_i and ask prices $a_i > b_i \geq 0$ within a trading period of 2 minutes, subject to the constraint that a resulting transaction would not take their bond inventory outside the permissible range of 0 to 2.

- A transaction occurs whenever a new bid (or ask) crosses the best posted ask (or bid). The trader with the posted offer is called the *maker* and the other trader is called the *taker*.

- The transaction price $q(t)$ is the posted price at time t, e.g., if new bid b_i equals or exceeds the lowest posted ask a_j at time t, then taker i purchases a unit from maker j at price $q(t) = a_j$.

As in the Call Market, traders in the CDA can aggregate their own private information with information gleaned from market activities, and choose their half-spreads $s > 0$ accordingly. That is, each trader will post a bid $b = \hat{V} - s$ and ask $a = \hat{V} + s$, but in the CDA traders can adjust $\hat{V}$ and s within the trading period in response to observed ongoing market activity. Another potentially important difference is that Call Market traders have to reason about counterfactuals, since they don't observe the clearing price before setting their bids and asks. By contrast, CDA traders see the prices at which other traders have so far made offers and trades (see Figure C.1 for an example CDA trader's screen from our laboratory implementation). That may make it easier to infer other traders' private information.

However, it has long been recognized that, absent heroic simplifications, game-theoretic models of such dynamic updating in CDA markets are intractable (e.g., Barelli et al. [2021], Friedman and Rust [1993a,b], Wilson [1985, 1987]). Consequently we simply offer the null hypothesis that the CM and CDA will produce the same market outcomes; rejections of that hypothesis may help inform subsequent theoretical and empirical work. In that spirit, we continue to use equation (4) as the trader's objective function in CDA as well as Call markets, and the resulting predictions about information acquisition, spread, volatility and liquidity derived in the next subsection thus apply to both the CM and CDA. We sometimes supplement those theory-based predictions by extrapolation or intuition-based conjectures on how CDA performance might differ from CM performance.[7]

2.3.2 Equilibrium Pricing and Trader Liquidity

Unlike in BDM, transaction prices in CM and CDA depend on other traders' bids and asks. Therefore, equation (4) is not a separable optimization problem. Instead, it defines the focal trader's best response to other traders' choices of (w, s), which determine (via aggregation of their private information) the variance of bond price q around expected bond value that the focal trader faces.

Indeed, since the price q faced by the focal trader incorporates other traders' private information, it will disproportionately often lie between the trader's own private expectation $\hat{V}$ and the perfect

[7] For example, as noted in the introduction, Ngangoué and Weizsäcker [2021] suggests that the CDA format may do a superior job of aggregating private information, but the evidence is mixed and comes from different contexts (e.g., exogenous private information) than ours.

foresight expectation $V(m)$. A trader who sets half-spread $s = 0$ and sets $a = b = \hat{V}$ as in BDM will disproportionately often sell when $q \in [\hat{V}, V(m)]$ and buy when $q \in [V(m), \hat{V}]$ — i.e., will sell low and buy high relative to the true expected value $V(m)$ — and thus incur expected losses. To mitigate such adverse selection, the trader will choose a half-spread $s > 0$. We say that *trader-level liquidity* is lower when her chosen spread is wider.

It is not straightforward to solve the best response problem (4) in the presence of adverse selection. For the sake of tractability, we assume that the focal trader has Normally distributed beliefs $f(q)$ about the price she will face. We seek *semi-consistent equilibrium* (SCE): in equilibrium each trader's beliefs about price q have mean and variance that coincide with the actual mean and variance that arise from the choices of other traders, although higher moments may differ.[8]

We now sketch the analysis detailed in Appendix A.3. Denoting the (subjective) variance of equilibrium price q around mean $V(m)$ as σ_q^2, in equation (40) we obtain the approximation

$$\sigma_q^2 \approx \frac{g^2 w^2}{3N^2}, \tag{5}$$

where N is the number of traders present and w is an index of other traders' chosen imprecision. Extensions of classical results on information aggregation show that the equilibrium spread satisfies the recursion

$$s = \frac{\sigma_o^2}{\sigma_o^2 + \sigma_q^2} H(s), \tag{6}$$

where σ_o^2 is the variance of the focal trader's own bond value estimate given only her own private information, $H(s) \equiv \hat{\sigma} E(x|x \geq \frac{s}{\hat{\sigma}}) = \frac{\hat{\sigma}\phi(\frac{s}{\hat{\sigma}})}{1-\Phi(\frac{s}{\hat{\sigma}})}$ for unit Normal density ϕ and cdf Φ, and $\hat{\sigma}^2 = \sigma_q^2 + \sigma_o^2$.

Starting with the first-order approximation

$$s \approx \frac{3.13 g w_o \sqrt{\frac{1}{12} + \frac{1}{3N^2}(\frac{w}{w_o})^2}}{0.27 + \frac{4}{N^2}(\frac{w}{w_o})^2}, \tag{7}$$

we numerically solve the recursion (6) for s and use it to numerically solve problem (4). As other traders' imprecision index w increases, the solution (the best response w_o) for given (g, k, N) parameters discontinuously jumps from 1.0 to a much smaller value. No fixed point ($w_o = w$) exists for that best response correspondence. That is, the model has no symmetric pure strategy equilibrium and so it predicts that we will not see symmetric choices of s and w. Instead, the model predicts that $n \geq 1$ of $N > 2$ traders will purchase rather precise information, and the other $N - n$ traders will purchase very little information. Comparing this result with Proposition 1, we can see that competitivity in CM and CDA makes traders' information acquisition choices more polarized than in BDM at given (k, g, N). This result is summarized in Prediction 1(i) below.

[8] SCE is a weaker equilibrium concept than, say, Perfect Bayesian equilibrium (PBE). However, PBE is difficult to work with here because the bond is a common value asset. Due to the No-Trade Theorem [Milgrom and Stokey, 1982], one can obtain a PBE with useful predictions (e.g., with positive trading volume) only by substantially complicating the model (e.g., with specific sorts of noise traders and/or with heterogenous risk aversion).

The foregoing implies that there is a threshold level $\tilde{w}(n, N)$ of the imprecision index faced by a focal trader at which she is indifferent to herself choosing low or high own imprecision w_o. Appendix A.3 analyzes the impact of the exogenous parameters (g, k, N) on the indifference condition. The implications are summarized in Prediction 1(ii) below.

Having analyzed how traders acquire information in best response, we now examine the determinants of half spread s. First, recall that $s = 0$ in BDM and $s > 0$ in more competitive CM and CDA market. Hence, we have spread increases with competitivity. Second, the endogenous variables w, w_o are predetermined when the focal trader chooses s. Thus we can use equation (7), confirmed by numerical analysis of the more precise equations for relevant parameter values, to see that s increases in own imprecision w_o and decreases in others' imprecision w. Third, the exogenous cost parameter k has no direct effect (but of course it may have an indirect impact via w and w_o). We obtain direct effects of g and N from inspection of (7) or numerical analysis, and control for indirect effects by including w and w_o when testing our predictions. The upshot is summarized in Prediction 1(iii) below.

Equation (5) indicates that equilibrium price is more efficient (i.e., is closer to its perfect foresight value $V(m)$) when g and w are smaller and the number of traders N is larger. Since other traders' imprecision index w decreases when the number n of traders choosing precise information increases, and n decreases with k, we predict that price efficiency increases with N but decreases with k (via w) and with g. We assume that the direct effect of g and N in equation (5) dominates their indirect effect through w. The net effect is summarized in Prediction 1(iv) below.

Information Aggregation. With the asymmetric pure equilibria in mind, now we discuss information aggregation. Let m^* denote the expected recovery rate m conditional on the pooled private information of all traders. Ignoring the remote possibility that all traders' revealed intervals are truncated on the same side, we have

$$m^* = \frac{\max\{m_{L,i}\} + \min\{m_{U,i}\}}{2}, \tag{8}$$

the midpoint of the intersection of the realized intervals of all traders $i = \{1, 2, ..., N\}$. Since $\max\{m_{L,i}\}$ is the largest of the realized lower endpoints $m_{L,i}$ among all traders, while $\min\{m_{U,i}\}$ is the smallest of their upper endpoints $m_{U,i} = m_{Li} + w_{o,i}$, that intersection has width

$$w_a = \min\{m_{U,i}\} - \max\{m_{L,i}\}. \tag{9}$$

Thus w_a indicates the imprecision of fully aggregated information about the unobserved m realization from *all* traders. Using equation (8), we can express fully aggregated expected bond value as

$$V(m^*) = 1 - g + gm^*. \tag{10}$$

Of course, actual information aggregation in a market will typically fall short of the ideal captured in m^*, w_a and $V(m^*)$.

How should exogenous variables (g, k, N) affect the imprecision w_a of the recovery-rate estimate m^* based on the aggregated information? That imprecision is proportional to the standard deviation σ_{m^*} of m^* which, using equation (10), is $\sigma_{m^*} = \frac{\sigma_{V(m^*)}}{g}$. We will see in the next subsection (in equation (11)) that price q closely approximates $V(m^*)$, so $\sigma_{m^*} \approx \frac{\sigma_q}{g}$. Using equation (5) above, we conclude that w_a is proportional to $\sigma_{m^*} \approx \frac{w}{\sqrt{3N}}$. The imprecision index w decreases with the number n of traders choosing precise information and, as we have seen, n decreases with k and increases with g. Thus we expect w_a to increase in k but to decrease in g (via w). Assuming that the direct effect from the denominator in the last expression dominates the indirect effect through w, we expect w_a to decrease in N. Prediction 1(v) below summarizes that reasoning.

We collect the foregoing in the following

Prediction 1. *In competitive markets CM and CDA, for the relevant range of parameters (k, g),*

(i) There are no symmetric pure strategy equilibria with positive trading volume with $N \geq 2$ traders; but there are asymmetric pure equilibria in which $n \geq 1$ traders pick small w_o and the other $N - n \geq 1$ traders pick w_o near 1.0.

(ii) The number n of traders choosing more precise information satisfies $\frac{\partial n}{\partial k} \leq 0$, $\frac{\partial n}{\partial g} \geq 0$, and $\frac{\partial n}{\partial N} \leq 0$.

(iii) Traders' chosen half spread s satisfies $\frac{\partial s}{\partial Competitivity} > 0$, $\frac{\partial s}{\partial g} > 0$, $\frac{\partial s}{\partial N} > 0$, $\frac{\partial s}{\partial w_o} > 0$, and $\frac{\partial s}{\partial w} < 0$, where w_o is one's own width choice and w is an index of others' width choices.

(iv) Price efficiency E (the closeness of price q to actual bond value $V(m)$) satisfies $\frac{\partial E}{\partial k} < 0$, $\frac{\partial E}{\partial g} < 0$, and $\frac{\partial E}{\partial N} > 0$.

(v) The imprecision w_a of fully aggregated information satisfies $\frac{\partial w_a}{\partial k} > 0$, $\frac{\partial w_a}{\partial g} < 0$ and $\frac{\partial w_a}{\partial N} < 0$.

2.4 Market Implications

The foregoing analysis has implications regarding the main market-level variables of interest: price volatility and liquidity. We now sketch how we obtain the relevant predictions.

2.4.1 Price Volatility

Transaction price q can be thought of as fully aggregated expected bond value $V(m^*)$ plus pricing error e. Data analysis is sharpened by further decomposing $V(m^*)$ into the perfect foresight value $V(m)$ given the unobserved true realization m, plus sampling error or discrepancy $d = V(m^*) - V(m)$. The pricing error e in turn can be written as the sum of mean-zero noise ε plus a possible bias term $\bar{e}$. The natural interpretation of $-\bar{e}$ is a risk premium, and in the empirical analysis (unlike in the previous exposition) we shall allow for the possibility that it is not zero. Thus we have the price decomposition

$$\begin{aligned} q &= V(m^*) + e \\ &= V(m) + d + \bar{e} + \varepsilon. \end{aligned} \tag{11}$$

This price decomposition allows us to decompose overall price volatility $\sigma_q^2 = Var(q)$ into $Var(V(m^*))$ plus $Var(e)$, assuming that (as seems reasonable) that e is independent of d and of (the iid uniformly distributed) m and thus of $V(m)$ and $V(m^*)$. We shall refer to $\sigma_r^2 = Var(V(m^*))$ as *efficient volatility* since it reflects efficient asset prices and arises solely from q tracking the fully aggregated expected bond value $V(m^*)$ across the aggregated private information embodied in m^*. By contrast, $\sigma_e^2 = Var(e)$ reflects pricing errors, so we shall refer to it as *inefficient volatility*.

Volatility can be further decomposed applying the variance operator to equation (11) to obtain Equation (12) below, assuming that $\bar{e}$ is constant. Equation (12) tells us that overall price volatility has four sources: (a) $Var(V(m))$, the unconditional variability of the true bond value $V(m) = 1 - g + gm$ across possible realizations of the actual recovery rate m; (b) $Var(d)$, the variability of the discrepancy between true and fully-aggregated bond value across realizations of m and the $[m_L, m_U]$'s; (c) $Cov(V(m), d)$, the covariance across realizations between the discrepancy and the true value; and (d) $Var(\varepsilon)$, the variance of additional pricing error ε. Source (a) comes from variations in fundamentals, sources (b) and (c) come from imperfect information about the true bond value, while (d) comes from behavioral noise due to incomplete aggregation of information as well as idiosyncratic pricing errors.

$$\begin{aligned}\sigma_q^2 &= \sigma_r^2 + \sigma_e^2 \\ &= Var(V(m^*)) + Var(e) \\ &= Var(V(m)) + Var(d) + 2Cov(V(m), d) + Var(\varepsilon),\end{aligned} \tag{12}$$

Equation (12) leads to several predictions about price volatility, some of which might at first seem counter-intuitive. If nobody purchases information (all individual $w_o = 1$ so fully aggregated $w_a = 1$) then $m^* = E(m) = 0.5$, a constant, and thus efficient volatility is $\sigma_r^2 \equiv Var(V(m^*)) = Var(V(0.5)) = 0$. When aggregated information becomes extremely precise ($w_a \to 0$), then $m^* \to m$ and $\sigma_r^2 \to Var(V(m)) = Var(1 - g + gm) = g^2 Var(m) = \frac{g^2}{12}$, since the variance of the uniform distribution on the unit interval is $\frac{1}{12}$. That is, more precise aggregated private information leads to higher efficient volatility, as q incorporates more of the volatility of the true bond value $V(m)$.

To better understand this result, recall that $\sigma_r^2 = Var(V(m)) + Var(d) + 2Cov(V(m), d)$. As w_a decreases from 1 to 0, component $Var(V(m)) = \frac{g^2}{12}$ remains constant given g while component $Var(d)$ decreases from $\frac{g^2}{12}$ to 0 and component $2Cov(V(m), d) = 2Cov(V(m), V(m^*)) - 2Var(V(m))$ increases from $0 - 2\frac{g^2}{12} = -\frac{g^2}{6}$ to $2\frac{g^2}{12} - 2\frac{g^2}{12} = 0$. Thus the increase in $2Cov(V(m), V(m^*))$ more than offsets the decrease in $Var(d)$. The analysis also shows that, holding w_a constant, efficient volatility is an increasing function of $g \geq 0$.

It is natural to expect that more precise private information and better aggregation will reduce behavioral noise amplitude and thus will reduce inefficient volatility σ_e^2. However, those same forces increase efficient volatility σ_r^2. Assuming that pricing errors have lesser amplitude,[9] we predict that

[9] As in our laboratory data, Table C.1 shows that σ_r^2 varies from 77 to 454, dominating σ_e^2, which ranges 78 to 132, in three out of the total four combinations of (k, g).

the efficient volatility effect will overshadow the inefficient volatility effect and so overall price volatility σ_q^2 will increase when our traders purchase more precise information and aggregate it better. In summary, we have

Prediction 2. *Price volatility depends on predetermined variables as follows:*

(i) *Efficient volatility* σ_r^2 *satisfies* $\frac{\partial \sigma_r^2}{\partial g} > 0$, $\frac{\partial \sigma_r^2}{\partial w_o} < 0$, *and* $\frac{\partial \sigma_r^2}{\partial w_a} < 0$.

(ii) *Inefficient volatility* σ_e^2 *satisfies* $\frac{\partial \sigma_e^2}{w_o} > 0$ *and* $\frac{\partial \sigma_e^2}{w_a} > 0$.

(iii) *Overall volatility* σ_q^2 *satisfies* $\frac{\partial \sigma_q^2}{\partial g} > 0$, $\frac{\partial \sigma_q^2}{\partial w_o} < 0$, *and* $\frac{\partial \sigma_q^2}{\partial w_a} < 0$.

2.4.2 Market Liquidity

A market is liquid to the extent that a trader can buy a unit immediately at a price that is close to the price at which she can immediately sell a unit. We therefore define market liquidity as the narrowness of the market spread. For the Call Market, the market spread is the best rejected ask price minus the best rejected bid price. For the CDA format, the market spread is the average best ask minus best bid in the order book over a certain time interval (e.g., within a second). Notice that, during the specified time interval, those bids and asks that rest in the order book are not executed. In that sense, they are similar to the rejected bids and asks in the Call Market. But CDA is different in that those bids and asks may be executed a few seconds later.

Since the market spread can also be described as the intersection of a fixed number (N) of individual bid-ask intervals, the factors that affect individual traders' half-spreads s in equation (7) should also affect market spread. Through that channel, smaller g narrows individual spread ($2s$) and thus market spread. The endogenous variable w_a, the imprecision of fully aggregated private information, has a similar impact on market spread. As we have seen, w_a is the width of the intersection of all privately revealed intervals, and as it gets smaller, bids and asks will cluster around the fundamental value $V(m)$ more tightly and that will narrow the market spread.

Lastly, increasing the number N of traders has two offsetting effects on the market spread: the intersection of a larger number of bid-ask intervals tends to be smaller (direct effect), but each individual spread will be larger (indirect effect) according to equation (7). We conjecture that the direct effect dominates the indirect effect. To summarize, we have

Prediction 3. *For the competitive markets (CM and CDA), the market spread* s *satisfies* $\frac{\partial s}{\partial w_a} > 0$, $\frac{\partial s}{\partial g} > 0$, *and* $\frac{\partial s}{\partial N} < 0$.

3 Experiment Design

Our laboratory experiment examines human subjects' information purchase choices and market outcomes under the three market formats (BDM, CM and CDA) presented in Section 2. The markets are implemented using oTree software (Chen et al. [2016]) programs written in LEEPS lab. For the convenience of our subjects, bond prices are rescaled from [0, 1] to [0, 100], and so information cost parameters are restated from $k = 0.001$ and 0.025 to $k = 0.1$ and 2.5. Figure 1 uses these restatements, and shows that optimal width choices for these parameters nicely span the feasible range, facilitating tests of the theoretical predictions.

Each round of the laboratory experiment follows the timeline laid out in Section 2. Each human trader is initially endowed with one unit of the bond, and sees the bond's default probability g for that round. Figure 3 illustrates for the case $g = 30\%$.

Figure 3: Public information: Default Probability

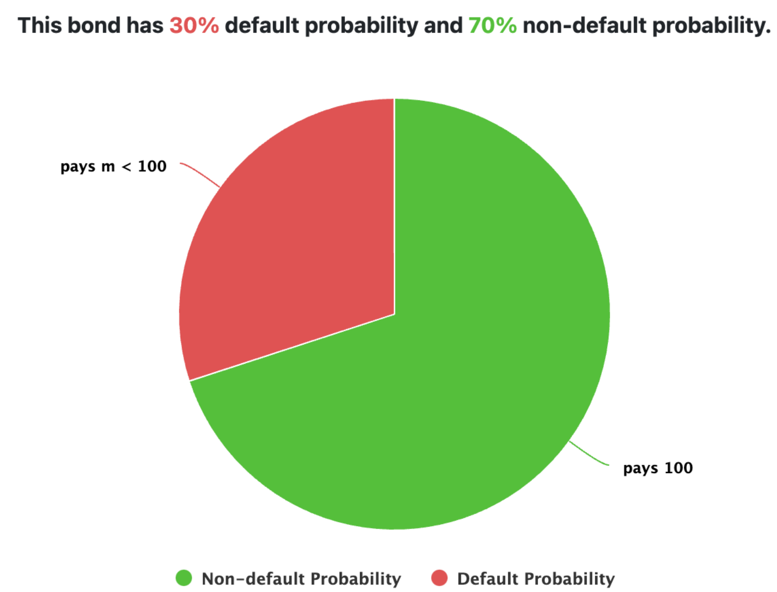
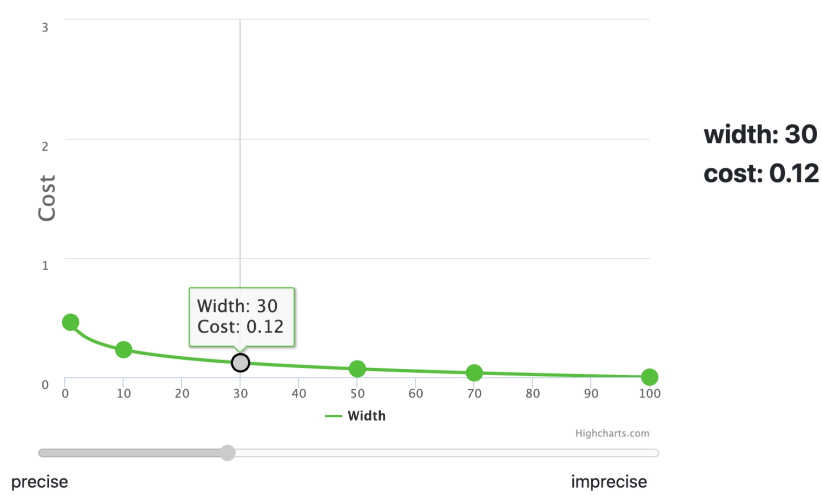


Figure 4: Width choice w when k=0.1



The next screen allows the player to purchase information about that round's value of m. As illustrated in Figure 4 for the treatment $k = 0.1$, the trader sees the cost function displayed as a green curve and uses the slider below it to choose (restated) width w at cost $C(w,k) = -k\ ln(w) \geq 0$, here $w = 30$ at cost $0.12 \approx -0.1\ ln(30/100)$. To simplify the trader's task and the data analysis, we restrict restated $w \in (0, 100]$ to the discrete subset shown as dots on the cost curve: {1, 10, 30, 50, 70, 100}. That subset includes a close approximation of the optimal width w^* for each of the four (k, g) combinations we use.[10] Note that, even though the (im)precision choice w is now discrete, the value of $m \in (0, 100)$ is still essentially continuous.

After confirming her choice of w, the trader receives her private information $m \in (m_L, m_U)$ as illustrated in Figure 5 for the case $m_L = 53.7, m_U \equiv m_L + w = 83.7$ following the $w = 30$ choice. Also, the screen shows the conditional expected values, here $V_L = 100(1 - g + gm_L) = 86.11$ and $V_U = 100(1 - g + gm_U) = 95.11$. The idea is to spare traders the effort (and possible error) of calculating the range of expected bond values on their own.

After that, traders choose a bid (buying price) b and ask (selling price) a by dragging colored balls on a scale (for BDM and CM) or by typing numbers into the boxes (for CDA, as illustrated at the bottom of Figure C.1). The software constrains these choices so that $0 \leq b \leq a \leq 100$ to avoid uninteresting irrationality. Choices outside the interval $[V_L, V_U]$ are allowed because they may reflect risk-aversion or risk-seeking.

Figure 5: Example of Private Signal and Expected Bond Values

Your private information about m: 53.7 ≤ m ≤ 83.7

Lowest expected bond value: 70% * 100 + 30% * 53.7 = **86.11**

Highest expected bond value: 70% * 100 + 30% * 83.7 = **95.11**

Next comes the opportunity to trade under one of the three formats. In a CDA round, traders know that the trading period lasts two minutes during which they can adjust their bids and asks whenever they want, and they see timely updates of the bid and ask order queues and transaction prices as illustrated in Figure C.1. In a CM round, after all traders enter their bids and asks, their screens display all bids (the demand schedule) and asks (supply), and the resulting clearing price q as in Figure 2. In a BDM round, traders see a roulette-like ball finally settle down to a random price q. In each case, traders see their final bond and cash holdings.

Finally, the true m and $V(m)$ for that round are displayed, default (or not) is determined and shown to all players, and final payoffs for that round are displayed to each trader individually. Default occurs if $y < g$ for an independent draw $y \sim U[0, 100]\%$; in this case, each bond unit pays $M = m$ and otherwise it pays $M = 100$. Consistent with equation (1), final payoff is $W - C(k, w) - \eta + r + hM$, where $-W$ is the participation fee (a sunk cost, detailed below), r is

[10]The cost of w is continuous at its upper endpoint, but the information value has a subtle discontinuity at that point. Just short of that endpoint, the revealed interval $[m_L, m_L + w]$ is almost always truncated either above (so $\hat{m} = 100 \times \frac{2}{3}$ by Lemma 1) or below (so $\hat{m} = 100 \times \frac{1}{3}$), but at the endpoint $\hat{m} = 100 \times \frac{1}{2}$. Therefore, to simplify our data analysis, we exclude choices of w slightly below 100. We also exclude choices below $w = 1$ (i.e., below 0.01 before rescaling) to keep traders from making costly trembles, but include the no-purchase choice $w = 100$. The other available choices are spaced evenly and include approximations of predicted unconstrained choices.

revenue from bond sales, η is the cost of bond purchases, $C(k, w)$ is the cost of chosen width w, and $h \in \{0, 1, 2\}$ is the number of bonds held after trade(s). In particular, participation fees $(-W)$ are used to cope with the relatively flat benefit and cost functions in our bond market parameterization. The idea is to make it less attractive to do nothing (i.e., neither trade nor purchase information). Such an additive shift in payoffs has no impact on a trader's expected payoff maximization, but it does increase the likelihood of a negative payoff in a given round.[11] Traders have about 30 seconds to review their payoff and its components before the next round begins.

Table 1: Summary of Production Sessions

Session	**BDMa**	**BDMb**	**BDMc**	**CMa**	**CMb**	**CMc**	**CDAa**	**CDAb**	**CDAc**	**CDAd**
Subjects(Silos)	19(2)	10(1)	8(1)	14(2)	11(1)	10(1)	16(2)	20(2)	10(1)	9(1)
Rounds(Blocks)	40(8)	40(10)	40(10)	30(6)	32(8)	32(8)	25(5)	24(6)	24(6)	24(6)
Block Parameters	0.1, 0.7	0.1, 0.3	0.1, 0.3	0.1, 0.7	0.1, 0.3	0.1, 0.3	0.1, 0.7	0.1, 0.3	0.1, 0.3	0.1, 0.3
(k,g)	0.1, 0.3	0.1, 0.7	0.1, 0.7	0.1, 0.3	0.1, 0.7	0.1, 0.7	0.1, 0.3	0.1, 0.7	2.5, 0.7	2.5, 0.7
	2.5, 0.7	0.1, 0.7/2.5, 0.7	2.5, 0.7	2.5, 0.7	2.5, 0.7	2.5, 0.7	2.5, 0.7	2.5, 0.7	2.5, 0.3	2.5, 0.3
	2.5, 0.7	2.5, 0.7	2.5, 0.7	2.5, 0.7	2.5, 0.7	2.5, 0.7	0.1, 0.3	2.5, 0.7	0.1, 0.7	0.1, 0.7
	0.1, 0.3	2.5, 0.7	0.1, 0.7	0.1, 0.3	0.1, 0.7	0.1, 0.7	0.1, 0.7	0.1, 0.7	2.5, 0.3	2.5, 0.3
	0.1, 0.7	0.1, 0.3	2.5, 0.3	0.1, 0.7	0.1, 0.3	0.1, 0.3		0.1, 0.3	2.5, 0.7	2.5, 0.7
	0.1, 0.7	0.1, 0.3	2.5, 0.3		2.5, 0.3	2.5, 0.3				
	0.1, 0.3	0.1, 0.7	2.5, 0.7		2.5, 0.7	2.5, 0.7				
		0.1, 0.7	0.1, 0.7							
		0.1, 0.3	0.1, 0.3							

Notes: In the first row, an entry such as 19(2) means that the 19 human subjects acted as traders in 2 permanently separated groups ("silos") of nearly equal size. In the second row, an entry such as 40(8) means that the 40 rounds were broken into 8 blocks of equal size, with parameter sets (k, g) listed sequentially in the rows below. One exception is that BDMb block 3 has 2 rounds of (0.1, 0.7) and 2 rounds of (2.5, 0.7) due to a technical glitch, although the results are perfectly fine, so we keep these four rounds. We exclude two CM rounds in the empirical analysis, one where the default probability was 39 (a typo in the input file) and another where some subjects' Zoom connections failed. Additionally, one CDA round is treated as a practice round and not included in the analysis.

Table 1 summarizes the experimental sessions, all conducted online during summer 2021 or summer 2024. Each experiment session uses one of the three market formats and is composed of 1 or 2 separate groups of players (called "silos"). Each silo has 7-11 players participating for all rounds: 40 rounds for each BDM silo, 30-32 rounds for each CM silo, and 24-25 rounds for CDA silos (since each round takes longer in the more competitive formats). That is, BDM and CM each has total 4 silos and CDA has 6 silos, with a total of 160 rounds of BDM, 124 rounds of CM and 146 rounds of CDA. Rounds are organized in blocks; each block is composed of 4 or 5 consecutive rounds with a fixed (k, g) parameter set. Block sequences are chosen to neutralize order effects; each parameter set of (k, g) is about as likely to precede as to follow any particular alternative, and they all occur in both early and late blocks. Each round uses independent sequences of random variables $(m, y, \rho_1, ..., \rho_N)$, where $\rho_i \sim U[0, 1]$ determines trader i's m_L as detailed at the end of Section 2.1. In that sense, each round is an independent implementation of the theoretical model and considered as a market when we conduct market-level analysis. To sharpen comparison across

[11]To reduce the chances of announcing a loss, we describe the participation fee as per-block, as defined in the next paragraph, rather than per-round. Specifically, the per-block fee P is chosen so that $-W = P/$[number of rounds in the block] is about 90% of the expected value of the single free bond endowed to each player each round.

formats, the sequences are drawn in advance for a session, and are recycled across sessions with different formats.

Each experiment session lasted about two hours. Subjects were recruited from the LEEPS lab pool using ORSEE software [Greiner, 2004]. After reporting to Zoom breakout rooms to anonymize trader IDs, subjects reviewed the written instructions, and then they all simultaneously viewed a video summarizing those instructions. After passing a quiz testing their understanding of the experiment (e.g., of bids and asks, or of the BDM truth-telling mechanism), subjects participated in two practice rounds and had a final opportunity to ask questions. They then served as traders in all rounds of the session. They could see the total number of traders in a silo by observing it in Zoom, but were not aware of the total number of rounds until the end. In CDA markets, the subjects could see a time clock showing how much time is left in the round. At the end of the session, each trader's payoffs were summed over all (nonpractice) rounds and converted to US Dollars at a pre-announced rate, with a cap of \$35.00 and a floor of \$5.00. Payments were via Venmo and averaged \$25.86 per subject.

4 Empirical Results

In this section we gather testable hypotheses, explain our empirical strategy for analyzing the laboratory data, and present the results of that analysis. Subsection 4.2 below does so for one of our main concerns, the impact on asset price volatility of the exogenous structural variables (g, k) and competitivity, as well as the impact on volatility of the endogenous information acquisition variables w_o and w_a. Section 4.3 does so for our other main concern, the impact on liquidity of those exogenous and endogenous variables. To set the stage, Section 4.1 briefly examines the endogenous variables in their own right and notes how they affect another aspect of market performance, informational (or price) efficiency.

4.1 Information Acquisition and Price Efficiency

Table 2 gathers testable hypotheses concerning information acquisition and price efficiency. It also summarizes the results of the relevant tests presented in Appendix B, most of which are consistent with our predictions. For example, as predicted in Proposition 1(ii)-(iii) and Prediction 1(ii), traders purchase more precise private information when it is cheaper (smaller k) and when the public information is more ominous (higher g). Consistent with Prediction 1(i), information purchase choices are more polarized/asymmetric across traders in more competitive markets. Consistent with Prediction 1(iv), prices are more efficient (closer to fundamental value and to perfect foresight value) with lower g and k and more traders present (higher N). These results underscore the generally high efficiency of our laboratory markets and encourage us to proceed with the empirical analysis in the next two subsections.

The main departures from theoretical prediction concern fully aggregated information imprecision w_a. Contrary to Prediction 1(v), it is higher with higher N, and contrary to conjecture it is higher with greater competitivity (under the CDA format than under the CM). In Section 4.3 and in the concluding Discussion below, we will speculate on the reasons for these and other departures.

See Appendix B for an explanation of the tests just reported, as well as other tests, data overviews and summary statistics.

Table 2: Information Hypothesis and Result Summary

Hypothesis	Source	Result	Reference
Information Acquisition:			
$\frac{\partial w^*}{\partial k} > 0$	Proposition 1 (ii)	Yes and significant	Table B.2 col 1
$\frac{\partial w^*}{\partial g} < 0$	Proposition 1 (iii)	Yes and significant	Table B.2 col 1
$\frac{\partial n/N}{\partial k} \leq 0$	Prediction 1 (ii)	Yes and significant	Table B.2 col 2
$\frac{\partial n/N}{\partial g} \geq 0$	Prediction 1 (ii)	Yes and significant	Table B.2 col 2
$\frac{\partial Polarization}{\partial Competitivity} > 0$	Prediction 1 (i)	Yes and significant	Table B.2 col 3
Price Efficiency (E):			
$\frac{\partial E}{\partial k} < 0$	Prediction 1 (iv)	Yes and significant	Table B.6 col 2&3
$\frac{\partial E}{\partial g} < 0$	Prediction 1 (iv)	Yes but insignificant	Table B.6 col 2&3
$\frac{\partial E}{\partial N} > 0$	Prediction 1 (iv)	Yes and significant	Table B.6 col 2&3
Additional		$\frac{\partial E}{\partial Competitivity} < 0$	Table B.6 col 2&3
Information Aggregation:			
$\frac{\partial w_a}{\partial k} > 0$	Prediction 1 (v)	Yes and significant	Table B.6 col 1
$\frac{\partial w_a}{\partial g} < 0$	Prediction 1 (v)	No but insignificant	Table B.6 col 1
$\frac{\partial w_a}{\partial N} < 0$	Prediction 1 (v)	No and significant	Table B.6 col 1
Additional		$\frac{\partial w_a}{\partial Competitivity} > 0$	Table B.6 col 1

Notes: Proposition 1 (i) implies point predictions that can be compared to the distributions of width choices shown in Figure B.1 for each combination of (k,g). Proposition 1 (iv) is the extreme point prediction that bids and asks equal $V(m^*)$ in BDM; Figure B.3 shows median deviations of actual individual asks and bids from $V(m^*)$. Prediction 1 (iii) is considered in Section 4.3 below.

4.2 Price Volatility

How do exogenous parameters and endogenous information acquisition affect asset price volatility? Table 3 summarizes relevant testable hypotheses from Prediction 2 in Section 2 and provides a preview of the test results. Recall that equation (12) decomposes overall volatility σ_q^2 into an efficient between-rounds component σ_r^2 and an inefficient within-round noise component σ_e^2, and that w_o denotes individual private information imprecision (width chosen by a given player in a given round). Recall also that in Table 3 hypotheses A1(i) and A3(i) reflect the view that when default risk g is high (as during a crisis), not only the high default risk itself but also the endogenous response of private and aggregate information to the ominous public information will elevate overall price volatility. Thus the information channel serves as an accelerator to increase overall volatility during crises. Besides these theory-based hypotheses derived in Section 2, the Table also includes additional conjectures on the impact of competitivity.

Table 3: Volatility Hypothesis and Result Summary

Hypothesis	Source	Result
Efficient Volatility		
A1(i) : $\frac{\partial \sigma_r^2}{\partial g} > 0$	Prediction 2 (i)	Yes and significant
A1(ii) : $\frac{\partial \sigma_r^2}{\partial w_a} < 0$	Prediction 2 (i)	Yes but insignificant
Additional		$\frac{\partial \sigma_r^2}{\partial Competitivity} = 0$
Inefficient Volatility		
A2: $\frac{\partial \sigma_e^2}{\partial w_o} > 0$	Prediction 2 (ii)	Yes and significant
Additional		$\frac{\partial \sigma_e^2}{\partial Competitivity} > 0$
Overall Volatility		
A3(i): $\frac{\partial \sigma_q^2}{\partial g} > 0$	Prediction 2 (iii)	Yes and significant
A3(ii): $\frac{\partial \sigma_q^2}{\partial w_o} < 0$	Prediction 2 (iii)	Yes and significant
Additional		$\frac{\partial \sigma_q^2}{\partial Competitivity} < 0$

Notes: All Results are from Table 4.

To test these hypotheses we run regressions of the form

$$\sigma^2 = \beta_0 + \beta_1 Info + InfoFormat'\boldsymbol{\beta}_2 + \beta_3 g + gFormat'\boldsymbol{\beta}_4 + Format_t'\boldsymbol{\beta}_5 + \gamma_s + \epsilon \tag{13}$$

where σ^2 is a component of (or is overall) price volatility, and $Format$ is a matrix of dummies for Call Market and CDA with BDM as the baseline. The unit of observation for between-round volatility σ_r^2 is a round, while for within-round volatility σ_e^2 and overall volatility σ_q^2 the unit of observation is a player-round for BDM and CM and is a transaction for CDA.[12] We exclude the information cost parameter k from equation (13) and subsequent regressions because our theory and hypotheses indicate that it has no *direct* impact. Of course, in both theory and practice, k can affect the outcome variables indirectly via information variable $Info$, which is implemented as w_a or w_o. For robustness, in columns (2), (4) and (6), we include an alternative measure of traders' information acquisition: *fraclw*, the fraction of players in a given round with the narrowest width choices, 1 or 10. Note that endogeneity issues regarding information acquisition, which commonly arise in field data, are alleviated in our regressions because acquisition choices are always made before trading starts and so are predetermined in our experiment. Variable γ_s captures fixed effects for silos, i.e., for particular cohorts of human subjects. Unless otherwise specified, all regressions use OLS with robust standard errors.

[12]We have also run regressions with data all at the player-round level, including the CDA sessions. The results are similar to those in Table 4 and are reported in the Appendix C Table C.2.

Table 4: Price Volatility Regression Results

	Between-round σ_r^2		Within-round σ_e^2		Overall σ_q^2	
	(1)	(2)	(3)	(4)	(5)	(6)
Aggr. Width (w_a)	−0.694 (1.918)					
Call Market × w_a	−5.828 (5.576)					
CDA × w_a	−2.328 (3.039)					
Own Width (w_o)			3.078*** (0.379)		−2.294*** (0.430)	
Call Market × w_o			−2.175*** (0.462)		−2.219*** (0.648)	
CDA × w_o			−3.080*** (0.461)		2.655*** (0.557)	
Default Rate (g)	8.161*** (0.922)	8.259*** (0.932)	0.255 (0.430)	−1.340** (0.595)	8.177*** (0.641)	11.470*** (1.345)
Call Market × g	0.485 (1.561)	0.776 (1.566)	0.216 (0.602)	1.294 (0.885)	1.033 (1.024)	1.598 (1.927)
CDA × g	−0.167 (1.405)	−0.465 (1.365)	0.713 (0.582)	2.211*** (0.738)	−0.455 (0.816)	−3.569** (1.440)
Fraclw		1.662 (1.240)		0.267 (0.532)		−1.801 (1.956)
Call Market × fraclw		0.379 (1.633)		−1.285 (0.891)		−1.673 (2.571)
CDA × fraclw		−0.722 (1.986)		−1.440** (0.706)		3.404 (2.105)
Call Market	−84.480 (91.780)	−155.400 (118.900)	286.900*** (51.650)	222.400*** (59.930)	−40.570 (86.020)	187.800 (173.700)
CDA	50.890 (87.090)	80.060 (110.900)	191.900*** (51.290)	55.160 (42.010)	−239.100*** (54.430)	−135.800 (131.000)
Constant	−149.900** (65.050)	−204.800*** (56.730)	−227.500*** (47.210)	−50.860 (49.690)	28.610 (82.820)	−177.100 (175.300)
Obs.	427	427	3447	1886	3447	1886
R^2	0.258	0.265	0.0937	0.0478	0.149	0.187

Notes: Dependent variable σ_r^2 is the squared deviation of $V(m^*)$ from $V(0.5) = E(V(m^*))$ in each round, and $\sigma_e^2 = \varepsilon^2$ is the squared deviation of price from $(V(m^*) + \bar{e})$, while σ_q^2 is the squared deviation of price from $(V(0.5) + \bar{e})$, where $-\bar{e} = -Ee$ is the empirical risk premium. Aggregate width w_a and individual own width w_o are defined in Section 2. Fraclw in each round is the percentage of traders choosing the narrowest widths (1 or 10). For BDM and CM, q is calculated as the midpoint of bid and ask by each player each round. For CDA, q is actual transaction price (usually several observations per round). $V(m^*)$, $V(0.5)$ and $\bar{e}$ are calculated at the round level. The baseline market is BDM. Silo fixed effects are included in all regressions. Robust standard errors are in parentheses. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 4 reports the results for price volatility. Columns (1) and (2) examine efficient/between-round price volatility $\sigma_r^2 = E(V(m^*) - V(0.5))^2$, where $V(0.5) = E(V(m^*))$ assuming $E(d)$ is zero (an excellent approximation, as shown in Appendix B Table B.7). Instead of calculating the volatility using squared deviations averaged across some subset of comparable rounds, which reduces the number of observations, we use $(V(m^*) - V(0.5))^2$ of each round as the dependent variable, so that the observation unit is consistently at the round level. A positive (negative) coefficient indicates that a rise in its variable leads to an increase (decrease) in σ_r^2. Consistent with Hypothesis A1(i), the coefficient for default probability g in column (1) is significantly positive at 8.161. Also as expected, the coefficient for w_a bears a negative sign, but it is insignificant. Likewise, the coefficient 1.662 of *fraclw* in column (2) has the predicted sign but is again insignificant.

In addition, we examine the impact of competitivity. Recall from the informal discussion in Section 2 that competitivity may have two opposing effects. Greater competitivity may encourage better aggregation of existing information, and thus increase efficient volatility and perhaps overall volatility. On the other hand, to the extent that it improves the dissemination of private information, greater competitivity will reduce the individual incentive to acquire costly private information. That in turn may reduce aggregate information, thereby reducing efficient and overall volatility. Thus the net impact of competitivity is an empirical question. In columns (1) and (2) of the Table, the coefficients for the CM and CDA dummies have opposite signs but are both insignificant. Thus, in our data, market competitivity does not appear to significantly affect efficient volatility.

Columns (3) and (4) of Table 4 examine inefficient/within-round volatility $\sigma_e^2 = Var(\varepsilon) = E(q - V(m^*) - \bar{e})^2$, so the dependent variable is $[q - V(m^*) - \bar{e}]^2$. As noted earlier, our volatility decomposition treats the risk premium $(-\bar{e})$ as constant, so we calculate $\bar{e} = E(e) = E[q - V(m^*)]$ separately for each round in forming the dependent variable.[13] For BDM and CM we use player-round level data for $V(m^*)$, use the midpoint between a player's bid and ask that round as q, and then take the average of their differences over players that round.[14] For CDA, transaction-round level data is used and q is the actual transaction price. Consistent with Hypothesis A2, column (3) of the Table reports a significantly larger within-round price volatility component σ_e^2 when traders choose wider width w_o, although this effect is weaker in CM and CDA. In column (4), only in the CDA market a lower fraction of players choosing small widths ($Fraclw$) leads to a higher σ_e^2, as expected. We do not have a hypothesis for the direct effect of g on σ_e^2. Note that the coefficients for the CM and CDA dummies are positive and significant in column (3), which implies that greater market competitivity significantly increases within-round volatility.

Finally, columns (5) and (6) of Table 4 examine overall price volatility $\sigma_q^2 = E(q - E(q))^2$, where $E(q) = V(0.5) + \bar{e}$. The dependent variable is thus $(q - V(0.5) - \bar{e})^2$. Consistent with Hypothesis A3, column (5) shows that σ_q^2 increases significantly when players choose more precise private information (smaller w_o) and when public information is more ominous (larger g). The latter effect is also evident in column (6). The coefficients for the CM and CDA dummies are negative in column (5), significantly so for CDA, suggesting that market competitivity decreases overall volatility. This result is consistent with our finding in Appendix B.2 that competitivity reduces information aggregation in the market, which leads to lower overall price volatility.

To dive deeper into efficient volatility, recall from equation (12) that it has three components, one of which, $Var(V(m))$, does not vary with w_a given g. Table 5 analyzes its two variable components: $Var(d)$ in columns (1) and (2), and $Cov(V(m), d)$ in columns (3) and (4). The dependent variable in the first two columns therefore is the squared deviation of $V(m^*)$ from $V(m)$ in each round. Consistent with the discussion in Section 2.4.1, the w_a coefficient in column (1) is significantly positive, and the coefficient for the fraction of players with narrowest widths, *fraclw*, in column (2)

[13] See Appendix C Table C.3 for an analysis of risk premium volatility using our laboratory data. We find that risk premium does not vary with w_a, which is reassuring. But it varies with default risk, $Fraclw$ and market format.

[14] For CM an alternative implementation of q is the actual clearing price; the results are similar. We report the midpoint implementation here to ensure direct comparability to the BDM baseline.

is significantly negative. Thus as the aggregate information becomes less precise (wider w_a, or lower *fraclw*), the deviation (of aggregated value $V(m^*)$ from perfect foresight value $V(m)$) increases. On the other hand, controlling for the information channel, there is little evidence that the g coefficient is positive or negative, except perhaps in CDA.

Table 5: Between-round Volatility Components by Round

	$Var(d)$		$Cov(V(m), d)$	
	(1)	(2)	(3)	(4)
Aggr. Width (w_a)	0.576***		−1.145***	
	(0.110)		(0.340)	
Call Market × w_a	−0.020		−0.329	
	(0.205)		(0.812)	
CDA × w_a	1.511		2.302	
	(0.983)		(1.449)	
Default Rate (g)	0.013	−0.018	−0.115	−0.052
	(0.017)	(0.025)	(0.075)	(0.068)
Call Market × g	−0.005	0.039	0.157*	0.030
	(0.018)	(0.027)	(0.082)	(0.075)
CDA × g	−0.011	0.163**	0.045	0.061
	(0.039)	(0.078)	(0.097)	(0.118)
Fraclw		−0.104***		0.235**
		(0.030)		(0.103)
Call Market × fraclw		0.038		−0.133
		(0.035)		(0.141)
CDA × fraclw		−0.344		−0.439
		(0.266)		(0.354)
Call Market	1.026	−7.078**	−9.941**	10.250
	(1.120)	(3.302)	(5.003)	(6.946)
CDA	0.147	−0.459	−5.349	21.380**
	(1.813)	(7.313)	(5.459)	(10.310)
Constant	−1.793*	9.205***	8.195*	−14.390**
	(1.059)	(3.150)	(4.629)	(5.947)
Obs.	427	427	427	427
R^2	0.506	0.149	0.159	0.0617

Notes: $Var(d)$ is the squared deviation of $V(m^*)$ from $V(m)$ for each round. $Cov(V(m), d)$ is $[V(m) - V(0.5)][V(m^*) - V(m)]$ for each round. Aggregate width w_a is defined as in the theory section. The baseline market is BDM. Silo fixed effects are included in all regressions. Robust standard errors are in parentheses. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Columns (3) and (4) of Table 5 report parallel results for the remaining efficient volatility component $Cov(V(m), d) = E(V(m) - V(0.5))(V(m^*) - V(m))$, again assuming $E(d) = 0$. The dependent variable is thus $(V(m) - V(0.5)) \times (V(m^*) - V(m))$ for each round. Consistent with the theoretical discussion in Section 2.4.1, the information coefficient signs are the opposite of those in columns (1) and (2): the w_a coefficient in column (3) is significantly negative and the *fraclw* coefficient in column (4) is significantly positive. Again, g has an insignificant impact. We conclude that the components of efficient volatility vary with private information in a manner consistent with theory.

4.3 Liquidity

We now turn to our other main concern, liquidity. Individual spreads and market spreads are our primary indicators of liquidity, as explained in Sections 2.3.2 and 2.4.2. Table 6 summarizes the relevant hypotheses and results. Hypothesis B1 is about trader-level half-spreads s and comes directly from equation (7) and Prediction 1(iii), using the harmonic mean w_{hm} as a proxy for other traders' heterogeneous width choices.[15] Hypothesis B2 is from Prediction 3 about market liquidity. A practical implication of Hypothesis B is that during a crisis when default risk is high, liquidity can be improved by increasing endogenous investment in private information.

Table C.4 in Appendix C offers summary statistics on individual traders' chosen spreads, denoted as $2s$ in the theoretical framework. That table pools across market formats but disaggregates by (k, g) treatment. Except for the highest cost/most ominous treatment $(2.5, 0.7)$, median individual spreads range from 5 to 10, and tend to be a bit smaller by the end of the round. Mean spreads are much larger than median, probably reflecting episodes where a player was not placing a serious bid and/or ask that makes trade a real possibility.

Table 6: Liquidity Hypothesis and Result Summary

Hypothesis	**Source**	**Result**
Individual spread s_i		
B1(i): $\frac{\partial s_i}{\partial w_o} > 0$	Prediction 1 (iii)	Yes and significant
B1(ii): $\frac{\partial s_m}{\partial w_{hm}} < 0$	Prediction 1 (iii)	Yes and significant
B1(iii): $\frac{\partial s_i}{\partial g} > 0$	Prediction 1 (iii)	Yes and significant
B1(iv): $\frac{\partial s_i}{\partial N} > 0$	Prediction 1 (iii)	Ambiguous and insignificant
B1(v): $\frac{\partial s_i}{\partial Competitivity} > 0$	Prediction 1 (iii)	Yes and significant
Market spread s_m		
B2(i): $\frac{\partial s_m}{\partial w_a} > 0$	Prediction 3	Yes; sometimes significant
B2(ii): $\frac{\partial s_m}{\partial g} > 0$	Prediction 3	Yes and significant
B2(iii): $\frac{\partial s_m}{\partial N} < 0$	Prediction 3	Yes (CDA only) and significant
Additional		$\frac{\partial s_m}{\partial Competitivity} = 0$

Notes: Individual spread Results are from Table 7 and Market spread Results are from Table 8.

To test Hypothesis B1 regarding trader-level liquidity, we combine data from all three market formats and regress the observed half-spread s_{it} of player i in round t on the relevant explanatory

[15] The aggregate width w_a used before incorporates the size of the market N as well as the variable of interest, w, the index for per capita imprecision. To find an appropriate proxy for w, we note that for given N the narrowest widths have a disproportionate influence on w_a. That asymmetry is better captured in the harmonic mean w_{hm} (which likewise puts greater weight on the smaller instances) than in the usual arithmetic mean.

variables as follows.

$$s_{it} = \beta_0 + \beta_1 w_{o,it} + w_{o,it} Format'_t \boldsymbol{\beta}_2 + \beta_3 w_{hm,it} + w_{hm,it} Format'_t \boldsymbol{\beta}_4 + \beta_5 g_t + g_t Format'_t \boldsymbol{\beta}_6 \\ + \beta_7 N_t + Format'_t \boldsymbol{\beta}_8 + \gamma_s + \epsilon_{it} \tag{14}$$

Table 7 reports the results. Consistent with Hypothesis B1(i-ii), the coefficients for a player's own choice w_o are positive and highly significant for initial, final, and mean spreads, and the coefficients for the harmonic mean of other players' widths are all significantly negative, although both effects are weaker in CM and CDA. Thus we find that trader-level liquidity is greater (smaller spread) when a player acquires more precise private information (smaller own w_o) and other traders acquire less precise information (larger harmonic mean of other traders' widths w_{hm}).

Table 7: Individual Spread Coefficient Estimates

	(1) Initial	(2) Ending	(3) Mean
Own width (w_o)	0.329***	0.329***	0.329***
	(0.019)	(0.019)	(0.019)
Call Market × w_o	−0.132***	−0.132***	−0.132***
	(0.026)	(0.026)	(0.026)
CDA × w_o	−0.236***	−0.301***	−0.282***
	(0.026)	(0.023)	(0.023)
Harmonic Mean of Others' Widths (w_{hm})	−0.097***	−0.097***	−0.097***
	(0.028)	(0.028)	(0.028)
Call Market × w_{hm}	0.176***	0.176***	0.176***
	(0.045)	(0.045)	(0.045)
CDA × w_{hm}	0.174***	0.091**	0.123
	(0.048)	(0.045)	(0.041)
Default Rate (g)	0.120***	0.120***	0.120***
	(0.024)	(0.024)	(0.024)
Call Market × g	−0.057	−0.057	−0.057
	(0.035)	(0.035)	(0.035)
CDA × g	0.080**	−0.080**	−0.009
	(0.039)	(0.036)	(0.034)
Size (N)	−1.810	0.281	−0.268
	(2.019)	(1.783)	(1.561)
Call Market	14.13***	9.948**	11.05***
	(4.801)	(4.411)	(4.060)
CDA	8.791**	12.15***	10.55***
	(3.547)	(3.217)	(3.010)
Constant	6.061	−10.67	−6.276
	(16.26)	(14.39)	(12.63)
Obs.	3489	3489	3489
R^2	0.334	0.280	0.294

Notes: Initial (resp. Ending, Mean) spread is an individual's first (resp. last, time-average) ask minus first (resp. last, time-average) bid in each round in CDA markets. These three spread variables coincide in BDM and Call markets. The harmonic mean of other players' width choices w_{hm} excludes a player's own width w_o. Size (N) is the number of players each round. The baseline market is BDM. Silo fixed effects are included in all regressions. Robust standard errors are in parentheses. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Consistent with Hypothesis B1(iii), the coefficients for g are also significantly positive, confirming that trader-level liquidity is larger (smaller spread) when public news is less ominous (smaller g). Also consistent with theory (compare maximization problems (2) and (4)) and Hypothesis B1(v), the coefficients for the CM and CDA dummies are positive and significant, which implies that market competitivity significantly increases individual spreads and thus reduces individual liquidity.

However, our data do not support Hypothesis B1(iv), that (due to adverse selection) traders provide more liquidity (smaller spread) when N is smaller. Instead, we find an ambiguous and insignificant market size effect. We see three possible reasons for that null result. (1) The theoretical basis for B1(iv) is weak: the relevant expressions include offsetting direct effects (N appears in both the numerator and denominator of relevant expressions), although we do control for the indirect effects via w_o and w_{hm} discussed in Section 2.3.2. (2) Our human traders may be less concerned with adverse selection than with other concerns omitted from our theoretical model, such as the intensity of perceived competition. (3) Size N ranges only from 7 to 11 across our sessions, and that variation might be insufficient to identify the true effect.

Table 8: Market Spread Coefficient Estimates

	(1) CM & CDA	(2) CM & CDA	(3) CDA	(4) CDA
Aggr. Width (w_a)	0.126		0.069	
	(0.079)		(0.093)	
CDA $\times$ w_a	-0.057			
	(0.121)			
Fraclw		-0.050^{***}		-0.049
		(0.013)		(0.031)
CDA $\times$ fraclw		0.001		
		(0.034)		
Default Rate (g)	0.054^{***}	0.042^{***}	0.060^{***}	0.064^{***}
	(0.016)	(0.014)	(0.021)	(0.021)
CDA $\times$ g	0.006	0.02		
	(0.027)	(0.025)		
Size (N)	2.255^{*}	1.781	-1.270^{***}	-1.275^{***}
	(1.170)	(1.147)	(0.283)	(0.286)
CDA	1.499	-0.557		
	(1.676)	(1.940)		
Constant	-22.910^{*}	-14.990	14.250^{***}	16.110^{***}
	(11.730)	(11.550)	(3.283)	(3.540)
Obs.	267	267	145	145
R^2	0.556	0.569	0.597	0.601

Notes: Market spread for CM is the lowest rejected ask minus the highest rejected bid in each round. For CDA, it is average of the lowest ask available minus the highest bid available in the order book in each second within a round. Aggregate width w_a is defined as in the theory section. Call Market is the baseline. Silo fixed effects are included in all regressions. Robust standard errors are in parentheses. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Now we turn to market spread analysis. Recall from Section 2 that market spread is the lowest rejected ask minus the highest rejected bid each round in CM, while in the CDA format it is the average within a round of the lowest ask minus the highest bid in the order book each second. Note that we do not report market spread for the BDM format because there it is not usefully distinguished from individual spread. Median market spreads range from 0.50 to 5.42; see Appendix C Table C.5 for detailed summary statistics.

To test Hypothesis B2 for market spread, we run regressions parallel to equation (14), replacing w_o and w_{hm} by the aggregate information variable $w_a = \min m_{U,i} - \max m_{L,i}$ or by the fraction of low width choices *fraclw*. Table 8 reports the results. The first two columns use all those data, while the last two columns use only CDA data. The significantly negative coefficient estimate for *fraclw* in column (2) supports hypothesis B2(i); the other relevant estimates (e.g., for w_a in columns (1) and (3)) all have the right sign but are not significant. Thus the data are not inconsistent with the prediction that market spreads narrow when aggregate private information is more precise. The significantly positive estimates for all the g coefficients supports Hypothesis B2(ii), the prediction that crisis conditions widen the market spread. Hypothesis B2(iii), that market spreads narrow when more traders are present, is supported in CDA markets, but not overall. The insignificant coefficients for the CDA dummy in columns (1) and (2) have opposite signs, so we have evidence that market liquidity is insignificantly affected by the more competitive CDA format.

As a robustness check, we also measure liquidity in terms of trading volume, and report the results in Table C.4 in Appendix C.4. We find that individual and market trading volume increases with individual (and aggregate) private information and decreases with ominous public information. However, the analysis cannot speak to the impact of competitivity because the most competitive format (CDA) inherently has more transactions than the less competitive format (CM). See Appendix C.4 for more details. On the whole, the liquidity results using trading volume are consistent with those using spreads.

5 Discussion

We construct a theoretical framework and a novel laboratory environment to investigate how asset price volatility and liquidity are shaped by private information acquisition. We examine how markets incorporate that information, contingent on market competitivity as well as on information cost, market size, and the economic state indicated by public information.

Several broad findings deserve highlights and interpretation. First, we find that the theory and laboratory data agree that overall price volatility increases when traders purchase more precise private information and when public information indicates a more ominous state. To interpret this result, recall that we are able to decompose overall volatility in our data into efficient and inefficient components. Inefficient volatility arises from noisy price fluctuations unrelated to fundamentals. In our experiment, we directly control fundamentals and hold them constant within a period, so we measure inefficient volatility in terms of price fluctuations within a trading round. Efficient volatility arises from the asset price tracking its fundamental value. In our experiment, fundamentals change from one round to the next, so we measure efficient volatility in terms of fluctuations across rounds. In the wider world, fundamentals are generally not directly observable but presumably they seldom change appreciably over short periods of time, such as a minute, a day, or possibly several weeks, while over longer periods of time, changes in fundamentals presumably drive price fluctuations.

Our distinction (easy to draw in the lab, more difficult in the field) between long-run or efficient volatility and short-run or inefficient volatility may be instructive to policy makers. The lesson is that overall price volatility, which is what they can observe, is not necessarily something to be minimized. It does make sense to minimize the inefficient component of volatility, perhaps by encouraging information acquisition (narrowing w_o) through lowering information cost k, especially during normal times when default risk g is low and inefficient volatility is high. Our results also suggest that increased (perceived) default risk during crises (or due to negative public signals) can directly raise overall price volatility and it can also indirectly increase it further by increasing private information purchases. Thus some of the increased overall volatility during crises comes from efficient volatility, so policy makers might choose to let it go. Nevertheless, if a policymaker wishes to dampen the overall volatility, one way is to raise information costs and thus reduce private information acquisition. Since much of the resulting decrease in overall volatility would come from the decrease in efficient volatility, the policy question is whether to sacrifice price efficiency in order to reduce overall volatility. That tradeoff seems worthy of investigation in future work.

A second broad finding is that liquidity (as indicated by the narrowness of bid/ask spread) also increases with more precise private information purchases, but it decreases with more ominous public information. An important policy implication is that, although (perceived) high default risk during crisis times (or due to negative public signals) can reduce liquidity, it can also increase information acquisition and aggregation and thus boost liquidity indirectly. Finding ways to reduce private information costs would further increase overall information acquisition and liquidity. Moreover, combining this liquidity result with the previous results, we find that during crises or when the default risk is perceived to be high, information acquisition and aggregation increases (see Proposition 1, Prediction 1, and Appendix B), which leads to a further increase in volatility and an improvement in liquidity—in that sense, there is also a tradeoff between volatility and illiquidity when we consider the endogenous choice of information acquisition. The opposite is true for normal times: lower default risk itself leads to lower overall volatility and higher liquidity, but the fact that lower default risk also reduces information acquisition will tend to offset the higher liquidity and to further lower volatility. Thus again there is tradeoff between illiquidity and volatility.

A third finding concerns competitivity. Most bonds are now traded in OTC dealer markets, where any given buyer (or seller) faces relatively little immediate peer competition. Our BDM format is an extreme case. What might be the impact of moving towards more competitive formats, more like our Call Market (CM) or Continuous Double Auction (CDA)? Our theory and evidence suggests that traders' private information choices would become more polarized (i.e., asymmetric), and that observed prices would become less volatile. Perhaps surprisingly, some of our evidence suggests a downside: the more competitive trading formats may impair price efficiency and liquidity.

For the most part, the laboratory results are consistent with our theoretical predictions, but there are some intriguing discrepancies. In particular, our Prediction 1(v) suggests that more traders will increase the precision of aggregate information. However, our data suggest the opposite effect. We conjecture that the main problem is with the theory. Our model perhaps puts too much emphasis on adverse selection, and does not allow for the possibility that traders simply bid more aggressively when they perceive more intense competition from a greater number of traders.

Subsequent theoretical and laboratory studies could explore more complex environments. For example, in our model and experiment, public information (the announced default probability g) is always fully credible. In the wider world, however, the credibility of public information can be a major issue. Future research could investigate by extending the theory and experiment to a repeated game environment. On a different front, we model highly rational risk-neutral agents, and focus narrowly on adverse selection. Those unrealistically stark assumptions enable us to obtain sharp predictions, and so are a good starting point. To the extent that actual humans (in the lab or in the field) produce systematic deviations from those sharp predictions, one might wish to extend the model in various ways. For example, by including an endowment effect, loss aversion, or risk aversion, one might be able to accommodate the positive bid-ask spread observed even in our minimally competitive BDM format.[16] One could also try to accommodate the deviations from predictions that are observed in the more competitive CM and CDA markets by incorporating ambiguity aversion and/or idiosyncratic motives to trade into the model. In particular, it would be difficult but perhaps not impossible to obtain useful predictions from perfect Bayesian equilibrium in a model of the CM that incorporated not only adverse selection but also heterogeneous risk aversion and/or personal bonuses for trading.

Future laboratory work could also explore heterogeneous information structures, although we conjecture that our qualitative results will be robust.[17] One could consider more complex connections between public information and private information. For example, private information on recovery rate m might affect default probability g. Also, one might consider time-varying unconditional variances across rounds in the experiment. More fundamentally, future investigators might wish to adapt our theoretical framework and experiments from bond markets to equity markets, where the different payoff structures may lead to different conclusions, e.g., benign public information might increase investors' private information acquisition instead of reducing it. We hope that our present contributions help pave the way to such new empirical and theoretical work.

[16] The argument in footnote 5 assumes that $\hat{V}$ is the same for the second bond unit as for the first. This assumption is correct for risk-neutral traders, and is almost correct for risk-averse (or risk-loving) expected utility maximizers when the bond units are small relative to income or wealth, as they are in our experiment. As noted at the end of the literature survey, Halevy et al. [2023] observe spreads analogous to ours and find that theirs are incompatible with risk aversion and indeed are incompatible with very general non-expected utility models.

[17] One suggestion is a random surplus, customarily attributed to noise traders (or the possible existence of a confused lab subject). Perhaps this might be done by extending the model of Kyle [1989]. Another suggestion is to give half the traders a small positive valuation increment. This also provides a positive trading surplus to evade the No-Trade result for common value assets, and might capture the idea that some human traders gain utility from actively trading, as well as from the take-home profits they might earn. A third possibility is to introduce heterogeneous risk aversion, which also creates a positive joint surplus.

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Appendix A Proofs and Mathematical Details.

A.1 Lemma 1

Unable to find off-the-shelf results covering the truncated cases, we derive formulas for cumulative distributions (F), densities (f) and expectations (E) summarized in the following Lemma. We use the notation $x_+ \equiv \max\{0, x\}$.

Lemma 1. *Given choice $w \in (0,1)$:*

1. *The lower endpoint $x = m_L$ has cumulative distribution function (cdf)*

$$\begin{aligned} F(x|w) &= 0, \qquad \textit{for } x < 0; \\ &= x + \frac{w}{2}, \textit{ for } x \in [0, 1-w); \\ &= 1, \qquad \textit{for } x \geq 1 - w. \end{aligned} \tag{15}$$

2. *The posterior density of m given chosen w and realized m_L is*

$$\begin{aligned} f(m|m_L, w) &= \frac{2}{w^2}(w-m)_+ \quad \textit{for } m_L = 0; \\ &= \frac{1}{w} \textit{ on } [m_L, m_U] \textit{ for } m_L \in (0, 1-w); \\ &= \frac{2}{w^2}(w + m - 1)_+ \textit{ for } m_L = 1 - w. \end{aligned} \tag{16}$$

3. *The corresponding expected values are*

$$\begin{aligned} \hat{m} \equiv E(m|m_L, w) &= \frac{w}{3}, \qquad \textit{for } m_L = 0; \\ &= m_L + \frac{w}{2}, \quad \textit{for } m_L \in (0, 1-w); \\ &= 1 - \frac{w}{3}, \qquad \textit{for } m_L = 1 - w. \end{aligned} \tag{17}$$

That is, the Bayesian posterior density of the true recovery rate is uniform over the realized interval in the untruncated case ($m_L > 0, m_U < 1$), and therefore has expected value $m_L + \frac{w}{2}$. The truncated cases have triangular densities. Due to truncation, the cdf for the lower interval endpoint has a mass of $\frac{w}{2}$ at its minimum value 0 and at its maximum value $1 - w$, but in between it is uniform of density 1.

Proof. Let the random variable $Z = X + Y$, where $X \sim U[-w, 0], Y \sim U[0, 1]$ represent respectively $-we$ and m. Thus Y has density $f_Y(y) = 1$ for $y \in [0, 1]$, and X has density $f_X(x) = \frac{1}{w} I_{[-w,0]}(x)$, where the indicator function $I_S(x) = 1$ if $x \in S$ and otherwise $I_S(x) = 0$.

By standard formulas for convolutions, Z has density

$$f_Z(z) = \int_{-\infty}^{\infty} f_X(z-y)f_Y(y)dy = \int_0^1 f_X(z-y)dy = \frac{1}{w}\int_0^1 I_{[-w,0]}(z-y)dy \qquad (18)$$

$$= \frac{1}{w}\int_{z-1}^{z} I_{[-w,0]}(u)du \qquad (19)$$

The last expression is $\frac{1}{w}$ times the length of $[-w,0]\bigcap[z-1,z]$. The two intervals do not intersect, and therefore the density is zero, when $z < -w$ or $z > 1$. When $z \in [0, 1-w]$, the first interval lies inside the second, so the intersection has length w and the density is $\frac{w}{w} = 1$. When $z \in [-w, 0]$, the intersection is $[-w, z]$ which has length $z + w$, so here $f_Z(z) = \frac{1}{w}(z+w)$. Finally, when $z \in [1-w, 1]$, the intersection is $[z-1, 0]$ which has length $1-z$, so here $f_Z(z) = \frac{1}{w}(1-z)$.

Thus the density increases linearly from 0 to 1 as z increases in $[-w, 0]$, is constant at 1 for $z \in [0, 1-w]$, and decreases linearly to 0 for $z \in [1-w, 1]$. It follows that $Pr[-w \le z \le 0] = \frac{w}{2} = Pr[1-w \le z \le 1]$.

Construct m_L by truncating z below at 0 and above at $1-w$. We just saw that each truncation binds with probability $\frac{w}{2}$, and in between m_L has the same density (1.0) as z. Hence the cdf is indeed $F(m_L) = 0, m_L < 0; F(0) = 0.5w; F(m_L) = m_L + 0.5w, m_L \in (0, 1-w); F(1-w) = 1, m_L \ge 1-w$, proving Lemma 1.1.

We prove Lemma 1.2 - 1.3 for the case $m_L = 0$; the case $m_L = 1-w$ is similar and the case $m_L \in (0, 1-w)$ is trivial. By Bayes Theorem,

$$f(m|m_L = 0) = \frac{Pr[m_L = 0|m]f(m)}{Pr[m_L = 0]} = \frac{Pr[we > m]\cdot 1}{\frac{w}{2}} = \frac{2}{w}[1 - \frac{m}{w}]_+ = \frac{2}{w^2}[w-m]_+,$$

since $Pr[we > m] = 0$ when $m > w$, and since $Pr[m_L = 0] = \frac{w}{2}$ by Lemma 1.1. Therefore

$$E[m|m_L = 0] \equiv \int_{-\infty}^{\infty} mf(m|m_L = 0)dm = \frac{2}{w}\int_0^w m[1 - \frac{m}{w}]dm = \frac{2}{w}\left[\frac{w^2}{2} - \frac{w^3}{3w}\right] = \frac{w}{3}. \ \square$$

A.2 Proposition 1

We now restate and prove the result on optimal trader behavior in the BDM format.

Proposition 1. *A risk-neutral trader facing the BDM procedure with default rate $g \in (0,1)$ and entropy cost parameter $k > 0$ will optimally choose*

(i) the unique width $w^* \in (0,1)$ that solves the cubic equation $w^2(2-w) = \frac{12k}{g^2}$ if $12k < g^2$, and otherwise will choose $w^* = 1$.

(ii) $\frac{\partial w^*}{\partial k} > 0$ for $0 < w^* \le 1$ and $0 \le k \le \frac{g^2}{12}$.

(iii) $\frac{\partial w^*}{\partial g} < 0$ for $0 < w^* \le 1$ and $0 \le g \le \sqrt{12k}$.

(iv) *Given the chosen w^* and subsequently revealed m_L, the trader will optimally choose bid and ask prices $b = a = \hat{V} \equiv E(M|m_L, w) = 1 - g + g\hat{m}$, for $\hat{m} \equiv E(m|m_L, w)$ as in Lemma 1.*

Proof. Write out the expected benefit function as

$$B(g, w) = \int_0^{1-w} \int_0^1 \left[\int_0^{\hat{V}} [2(1 - g + gm) - q]f(q)dq + \int_{\hat{V}}^1 qf(q)dq \right] f(m|m_L)f(m_L)dmdm_L. \tag{20}$$

To see this, note that the expectation must be taken with respect to (a) the uniformly distributed market price q under BDM, (b) the realized recovery rate m conditioned on m_L and the chosen w, and (c) the signal m_L whose distribution depends on the chosen w. Hence we have a triple integral. The integrand has two pieces. By equation (1), the integrand represents the receipts q from selling the endowed bond when $q > \hat{V}$, and it represents the expected payout on two bonds held less the price of the purchased bond, $2(1 - g + gm) - q$, when $q < \hat{V}$.

To evaluate (20), note that the bracketed inner integrals are taken with respect to q, which has a uniform density on $[0, 1]$. Using the notation $V(m) = 1 - g + gm$, the bracketed term therefore is

$$\left[2V(m)\hat{V} - \frac{q^2}{2}|_0^{\hat{V}} + \frac{q^2}{2}|_{\hat{V}}^1 \right] = 2V(m)\hat{V} - \hat{V}^2 + \frac{1}{2}. \tag{21}$$

The middle integral is taken with respect to the $f(m|m_L)dm$; since all else is constant, the only effect on the right hand side of (21) is to replace $V(m)$ by its conditional expectation $\hat{V}$. Thus the triple integral reduces to

$$\int_0^{1-w} [\hat{V}^2 + \frac{1}{2}]f(m_L)dm_L = \frac{1}{2} + \int_0^{1-w} \hat{V}^2(m_L)dF(m_L). \tag{22}$$

The last integrand is written as a function of m_L to remind us that $\hat{V} = 1 - g + g\hat{m}$ where (by Lemma 1) $\hat{m} = m_L + \frac{w}{2}$ for $m_L \in (0, 1 - w)$ but that $\hat{m} = \frac{w}{3}$ when $m_L = 0$, and $\hat{m} = 1 - \frac{w}{3}$ when $m_L = 1 - w$. The Stieltjes integral expression $dF(m_L)$ is to remind us of equation (15), which assigns mass points at $m_L = 0$ and $1 - w$, each of mass $\frac{w}{2}$, and elsewhere $f(m_L) = 1$. Thus we can write out equation (22) explicitly for $w < 1$ as

$$\begin{aligned} & \frac{1}{2} + \frac{w}{2}\hat{V}^2(0) + \frac{w}{2}\hat{V}^2(1 - w) + \int_0^{1-w} \hat{V}^2(m_L)dm_L \\ =& \frac{1}{2} + \frac{w}{2}[1 - g + g\frac{w}{3}]^2 + \frac{w}{2}[1 - g + g(1 - \frac{w}{3})]^2 + \int_0^{1-w} [1 - g + g(m_L + \frac{w}{2})]^2 dm_L \\ \equiv & \quad B(g, w). \end{aligned} \tag{23}$$

Tedious but straightforward algebra reveals that the benefit function is

$$B(g,w) = \frac{3}{2} - g + \frac{1}{3}g^2 - \frac{1}{12}g^2w^2 + \frac{1}{36}g^2w^3. \tag{24}$$

Recall that the overall optimization problem is

$$\max_w \Pi = W - C(k,w) + B(g,w), \tag{25}$$

where W is the initial wealth including sunk cost, $C(k,w) = -k\ln w$ is the entropy cost of chosen imprecision (interval width) w, and $B(g,w)$ is now known to be given by equation (24) for $w \in (0,1)$. The first order condition $-\frac{\partial}{\partial w}C(k,w) = -\frac{\partial}{\partial w}B(g,w)$ is therefore

$$\frac{k}{w} = \frac{1}{12}g^2w(2-w). \tag{26}$$

Equation (26) can be rewritten as

$$w^2(2-w) = \frac{12k}{g^2}. \tag{27}$$

The left hand side $w^2(2-w)$ strictly increases from 0 to 1 for $w \in [0,1]$, and therefore the equation has a unique solution $w^* \in (0,1)$ for parameters such that the right hand side $\frac{12k}{g^2} < 1$. It is straightforward to verify that the SOC holds in this case, and that the corner solution, $w = 1$, solves the maximization problem when $\frac{12k}{g^2} \geq 1$. Thus we have proved part (i) of Proposition 1. Parts (ii) and (iii) follow from the monotonicity of the left and right hand sides of equation (27) over the relevant ranges of their variables. Part (iv) follows from the variant of the standard argument noted in footnote 5. □

A.3 Prediction 1

We now detail the approximations and numerical solutions we used to reach Prediction 1 in the competitive markets.

Prediction 1. *In competitive markets CM and CDA, for the relevant range of parameters* (k,g)*,*

(i) There are no symmetric pure strategy equilibria with positive trading volume with $N \geq 2$ *traders; but there are asymmetric pure equilibria in which* $n \geq 1$ *traders pick small* w_o *and the other* $N - n \geq 1$ *traders pick* w_o *near 1.0.*

(ii) The number n *of traders choosing more precise information satisfies* $\frac{\partial n}{\partial k} \leq 0$, $\frac{\partial n}{\partial g} \geq 0$, *and* $\frac{\partial n}{\partial N} \leq 0$.

(iii) Traders' chosen half spread s *satisfies* $\frac{\partial s}{\partial Competitivity} > 0$, $\frac{\partial s}{\partial g} > 0$, $\frac{\partial s}{\partial N} > 0$, $\frac{\partial s}{\partial w_o} > 0$, *and* $\frac{\partial s}{\partial w} < 0$*, where* w_o *is one's own width choice and* w *is an index of others' width choices.*

(iv) Price efficiency E (the closeness of price q to actual bond value $V(m)$) satisfies $\frac{\partial E}{\partial k} < 0$, $\frac{\partial E}{\partial g} < 0$, and $\frac{\partial E}{\partial N} > 0$.

(v) The imprecision w_a of fully aggregated information satisfies $\frac{\partial w_a}{\partial k} > 0$, $\frac{\partial w_a}{\partial g} < 0$ and $\frac{\partial w_a}{\partial N} < 0$.

Argument:

Half Spread. The reasoning that leads to Prediction 1.iii begins with a classical result on information aggregation (e.g., DeGroot, 1970): the posterior expectation given two independent normally distributed signals $x_1 \sim N(x, \sigma_1)$ and $x_2 \sim N(x, \sigma_2)$ is the precision-weighted mean

$$E(x) = \frac{\tau_1}{\tau_1 + \tau_2} x_1 + \frac{\tau_2}{\tau_1 + \tau_2} x_2, \tag{28}$$

where precision is the reciprocal of variance, $\tau_i = \sigma_i^{-2}$. Suppose that a trader regards the market price q as partially revealing the bond value, with distribution $q \sim \mathcal{N}(V(m), \sigma_q^2(N, w))$ (assuming no risk premium). That is, each trader's subjective distribution is unbiased Normal with precision $\tau_q = \sigma_q^{-2}$ that depends on the number of other traders $N-1 \geq 1$ and their aggregated chosen imprecision w. Note that we do not impose homogeneity of chosen widths by other traders in the model. As noted in the text (and explained in more detail below), the empirical counterpart of w is the harmonic mean w_{hm} of other players' width choices, recognizing that those choices are likely to be heterogeneous. Suppose also that the focal trader purchases a possibly different width $w_o > 0$. It will generate a signal $\hat{m} = E(m|w_o, m_L)$ with precision that we will write as $g^2 \tau_o$, so that the corresponding estimate $\hat{V} = 1 - g + g\hat{m}$ of asset value has precision τ_o.

For the moment also suppose, counterfactually, that the trader were able to observe the Call Market price q as well as her private information $\hat{m}$. According to equation (28) her posterior expectation would be

$$E[V|\hat{m}, q] = \frac{\tau_o \hat{V} + \tau_q q}{\tau_o + \tau_q}. \tag{29}$$

Dropping the last counterfactual, we acknowledge that trader can't observe the Call Market price q before she sets her bid and ask b and a. However, she should anticipate that only market prices $q \geq a$ and $q \leq b$ will enable her to trade, and her optimal half-spread s should reflect her posterior expected bond value given that she does trade. More specifically, we suppose that she chooses her ask price $a \equiv \hat{V} + s$ so that any clearing price q higher (resp. lower) than a will lead to a positive (resp. negative) posterior expected profit. Thus we impose the break-even condition

$$a \equiv \hat{V} + s = E[V|\hat{m}, q \geq a] = \frac{\tau_o \hat{V} + \tau_q E[q|q \geq a]}{\tau_o + \tau_q}. \tag{30}$$

Likewise, her bid should satisfy

$$b \equiv \hat{V} - s = E[V|\hat{m}, q \leq b] = \frac{\tau_o \hat{V} + \tau_q E[q|q \leq b]}{\tau_o + \tau_q}. \tag{31}$$

The half spread we seek therefore is defined implicitly by the equation

$$2s = a - b = \frac{\tau_q}{\tau_o + \tau_q}[E(q|q \geq \hat{V} + s) - E(q|q \leq \hat{V} - s)]. \tag{32}$$

To solve equation (32), we write out the assumption of unbiased normal beliefs as $q = V(m) + e = \hat{V} + d + e$, where $e \sim N(0, \sigma_q^2)$ and $d \sim N(0, \sigma_o^2)$ are independent. Hence our trader believes that the clearing price she will face is $q \sim N(\hat{V}, \hat{\sigma}^2)$ where $\hat{\sigma}^2 = \sigma_q^2 + \sigma_o^2$. That is, the variance $\hat{\sigma}^2$ of clearing price around her private estimate is the variance σ_q^2 of clearing price around the unobserved true mean plus the variance σ_o^2 of the true mean around her private estimate.

Using the standard notation $\phi(x)$ and $\Phi(x)$ for the unit normal density and CDF, note that

$$E(x|x \geq c) = \frac{\int_c^\infty x\phi(x)dx}{1 - \Phi(c)} = \frac{\phi(c)}{1 - \Phi(c)}. \tag{33}$$

The last expression used change-of-variable $u = 0.5x^2$ to integrate the numerator: $(2\pi)^{-1} \int_{0.5c^2}^\infty e^{-u}du = (2\pi)^{-1}[0 - (-e^{-0.5c^2})] = \phi(c)$. Hence the bracketed term in equation (32) is

$$\begin{aligned} E(q|q \geq \hat{V} + s) - E(q|q \leq \hat{V} - s) =& \hat{V} + \hat{\sigma}E(x|x \geq \frac{s}{\hat{\sigma}}) - [\hat{V} - \hat{\sigma}E(x|x \leq \frac{-s}{\hat{\sigma}})] \\ =& 2\hat{\sigma}E(x|x \geq \frac{s}{\hat{\sigma}}) \\ =& 2\hat{\sigma}\frac{\phi(\frac{s}{\hat{\sigma}})}{1 - \Phi(\frac{s}{\hat{\sigma}})} \end{aligned} \tag{34}$$

Inserting (34) into (32) and recalling that precision is $\tau_i = \sigma_i^{-2}$, we obtain

$$\begin{aligned} s =& \frac{\tau_q}{\tau_o + \tau_q}\hat{\sigma}\frac{\phi(\frac{s}{\hat{\sigma}})}{1 - \Phi(\frac{s}{\hat{\sigma}})} \\ =& \frac{\sigma_o^2}{\sigma_o^2 + \sigma_q^2}H(s), \end{aligned} \tag{35}$$

where $H(s) \equiv \hat{\sigma}E(x|x \geq \frac{s}{\hat{\sigma}}) = \frac{\hat{\sigma}\phi(\frac{s}{\hat{\sigma}})}{1-\Phi(\frac{s}{\hat{\sigma}})}$ and $\hat{\sigma}^2 = \sigma_q^2 + \sigma_o^2$.

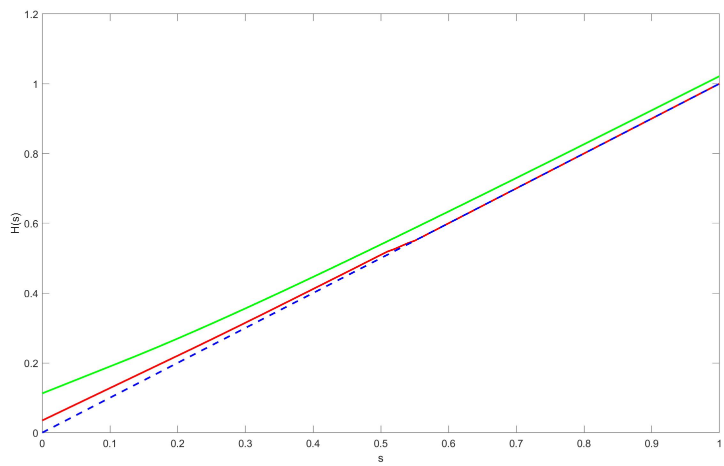
To see that equation (35) and hence equation (32) has a unique solution s^* for given $\sigma_q^2 + \sigma_o^2 > 0$, note first that the obvious inequality $E(x|x > c) > c$ implies that $H(s) >$

$\hat{\sigma}[s/\hat{\sigma}] = s$, i.e., H lies above the diagonal. Applying L'Hospital's rule to (33) yields

$$E(x|x \geq c) \to \frac{-c\phi(c)}{-\phi(c)} = c \quad \text{as } c \to \infty, \tag{36}$$

which implies that $H(s)$ is asymptotically tangent to the diagonal. For a visual confirmation, see Figure A.6, which graphs $H(s)$ for two different values of $\hat{\sigma}$.

Figure A.6: $H(s)$ as a function of s.



Notes: Red (green) line graphs $H(s)$ for $\hat{\sigma} = 0.07$ ($\hat{\sigma} = 0.20$), and dashed blue line graphs s (the diagonal line).

The desired result now follows from the intermediate value theorem. At $s = 0$ the LHS of equation (35) is 0 while the RHS is positive. For sufficiently large s, the LHS s exceeds the RHS since $\frac{\sigma_o^2}{\sigma_o^2+\sigma_q^2} < 1$. Since the functions are continuous, there must be a point s^* where the LHS=RHS. This point is unique since the slope of the LHS is 1, which exceeds the slope of the RHS, which is bounded above by $\frac{\sigma_o^2}{\sigma_o^2+\sigma_q^2} < 1$.

Solving equation (35) numerically is not always straightforward, because the numerator and denominator of $H(s)$ both go to zero quickly at relevant values of s when $\hat{\sigma}$ is small. We can alleviate the problem by canceling a common factor in the numerator and denominator. Starting from equation (33): $E[x|x \geq c] = \frac{\phi(c)}{1-\Phi(c)}$, where $c = \frac{s}{\hat{\sigma}}$, we can approximate the denominator in various ways. Zelen and Severo (1964) develop n-th order numerical approximations on Normal distribution. Their first order approximation is $\Phi(x) \approx 1 - \phi(x)\frac{.32}{1+.23x}$ with error of order x^{-2}. Hence the denominator in equation (33) is $1 - \Phi(c) \approx \phi(c)\frac{.32}{1+.23c}$. Cancelling the tiny common factor $\phi(c)$, we get $E[x|x \geq c] \approx \frac{1+.23c}{.32} \approx 3.13+0.73c$. It follows that, for small $\hat{\sigma}$,

$$s \approx \frac{3.13\hat{\sigma}\sigma_o^2}{\sigma_q^2 + 0.27\sigma_o^2}. \tag{37}$$

We need to express the σ's in equations (35) and (37) in terms of the choices (w, w_o) and structural parameters (g, N). Although its distribution is not Normal, textbook formulas tell us that $\hat{V} = 1 - g + g\hat{m}$ has variance $\sigma_o^2 = g^2\sigma_{\hat{m}}^2 = \frac{g^2 w_o^2}{12}$ around the true value $V(m)$ when there is no truncation so that $[m|w_o, m_L]$ has a uniform distribution. In the next subsection below, labelled Variance Approximations, we will derive the approximation $\sigma_q^2 \approx \frac{g^2 w^2}{3N^2}$ from equations (39) and (40). Here, inserting these expressions into equation (37) and simplifying slightly, we have

$$s \approx \frac{3.13 g w_o \sqrt{\frac{1}{12} + \frac{1}{3N^2}(\frac{w}{w_o})^2}}{0.27 + \frac{4}{N^2}(\frac{w}{w_o})^2}. \tag{38}$$

In Matlab, we solve for $s(N, g, w, w_o)$ numerically in equation (35) using the expressions just given for $\hat{\sigma}^2 = \sigma_q^2 + \sigma_o^2$ and using (38) to initialize the recursion. Prediction 1.iii follows from observing how the variables (N, g, w, w_o) enter equation (35) or, more explicitly, equation (38).

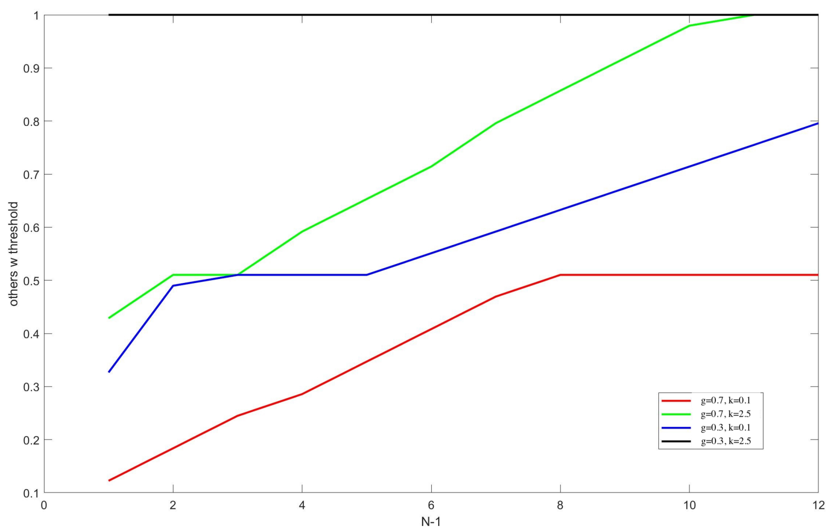
Then, plugging the solved value of s into the limits of the inner integrals in the objective function equation (4), we integrate with respect to q to obtain the expected benefit conditional on the realized m_L. Integrating out m and m_L using the truncated density $f(m|m_L)$ and the truncated distribution function $F(m_L)$ given in Lemma 1, we obtain a numerical approximation of the expected benefit $B(g, w_o|w, N)$. Given that benefit function and entropy cost $C(k, w_o)$, we solve marginal benefit = marginal cost to find a w_o that is a best response to other players' aggregated chosen imprecision w, given the exogenous parameters (k, g, N).

A fixed point to that best response correspondence would represent a symmetric Nash equilibrium in information purchase. However, for (g, N) fixed at relevant values, we obtain a benefit function $B(g, w_o|w, N)$ for most w's that is almost constant in w_o, increasing very gradually as we decrease w_o. For relevant k, the cost function $C(w, k)$ is also nearly constant (close to zero) over most of its range, but increases rapidly as as we decrease w_o towards its minimal value (set at $w_o = 0.01$ in the experiment before being re-scaled by 100 to 1.0). Hence the objective function, $B - C$ plus a constant W, is rather flat but has two relative maxima, one near $w_o = 1$ and the other near its minimal value.

Consequently, as we vary the choice w of other traders, the focal trader's best response jumps discontinuously from the relative maximum with w_o near 1 to the relative maximum near 0. Thus the best response does not intersect the diagonal $w_o = w$, and there is no fixed point. That is, there is no symmetric Nash equilibrium in pure strategies, as claimed in Prediction 1.i.

This conclusion comes from numeric simulations of a model that assumes all other traders choose the same value of w, but that is not an essential feature. The point is that, however many other traders there are and whether or not they make homogeneous choices on information acquisition and bidding strategies, the price that a given trader anticipates facing has some precision τ_q. There is a threshold in that precision (expressible reciprocally in terms of either w or σ_q) below which the trader's best response is to purchase lots of private information, and above which her best response is to purchase very little information. The upshot is that the only pure strategy NE are asymmetric — some fraction $\frac{n}{N} > 0$ of traders purchase precise information, and the other traders purchase very little. The fraction is determined by the indifference condition that no trader can profitably switch roles. The first part of Prediction 1.ii follows, and the dependence of n on k and g follows from the discussion below of Figure A.7.

Figure A.7: Threshold w as a function of (g, k, N).



The indifference condition that no trader can profitably switch roles implies a threshold level of imprecision $\tilde{w}$. Figure A.7 shows, for relevant (g, k) parameters, the threshold imprecision $\tilde{w}$ as a function of the total number $N-1$ of other traders. If the index w is small enough, i.e., below $\tilde{w}$, then it is not worthwhile for the focal trader to purchase costly information herself; and above the threshold, she will acquire more information.

The threshold $\tilde{w}$ varies with (g, k, N). First, where not maxed out at $w = 1$, the $\tilde{w}$ lines for (g, k) combinations slope upward in N. The intuition is that aggregating over more traders compensates for reduced precision by individual other traders. Second, as announced default risk g increases, all else equal, the threshold decreases. That is, when default risk is higher as in the red line compared to the blue line (or the green line compared to the black line) in Figure A.7, it takes more precise information from other traders for a given trader to forgo her own information acquisition. Thus in asymmetric equilibrium, a lower $\tilde{w}$ when g increases may translate to a larger number n of traders purchasing precise information or/and more precise information acquisition by acquirers, given that N and k are unchanged. After all, as perceived default risk increases, private information can become more crucial to traders' payoff. Third, when information cost parameter k is lower, $\tilde{w}$ is smaller, and thus similarly we predict a larger n, as evidenced by the green and red (or blue and black) lines in the Figure. This point is summarized in Prediction 1(ii) below.

Prediction 1.iv arises from the property that in (self-confirming) equilibrium, price q has variance σ_q^2 around mean $V(m)$, where the dependence of σ_q on (g, k, N) is elaborated below.

Variance Approximations. We now derive the approximation for σ_q mentioned before equation (38). The key is to show that with $N \geq 2$ traders, and with all other traders choosing the same $w \in [0, 1]$, the prices faced by a given trader will convey information about the true m through aggregate m^* with approximate precision

$$\tau_{m^*} = \sigma_{m^*}^{-2}(N, w) = 3\frac{N^2}{w^2}. \tag{39}$$

It follows that

$$\sigma_q(N, w) \approx \sigma_{V(m^*)} \approx g\sigma_{m^*} = \frac{gw}{\sqrt{3}N}, \tag{40}$$

since price $q = V(m^*) + e$ (see equation (11); recall that e is independent of $V(m^*)$ and $Var(e)$ is small) and since fully aggregated bond value is $V(m^*) = 1 - g + gm^*$.

To obtain (39) we reason as follows. The other $n = N - 1$ traders draw i.i.d. realizations $e_i \sim U[0, 1]$ to obtain private information intervals $[m_{L,i}, m_{U,i}] = [m - we_i, m - we_i + w]$, assuming no truncation. The intersection of n such intervals is $[m - w \min_i e_i, m - w \max_i e_i + w]$, which has width $w(1 - \max_i e_i + \min_i e_i)$. A well known property of order statistics for the uniform distribution on [0,1] is that $E \min e_i = \frac{1}{n+1}$, and symmetrically, $E \max e_i = 1 - \frac{1}{n+1}$. Hence the expected width of the intersection is $\frac{2w}{n+1}$. Now equation (39) follows from combining that last expression with the well known expression $\sigma_{m^*}^2 = \frac{z^2}{12}$ for variance of a uniform distribution of width z, and here $z = \frac{2w}{n+1} = \frac{2w}{N}$. Equation (40) follows from noting that m^* is multiplied by g in the expression for $V(m^*)$.

The idea is to form an upper bound that assumes complete aggregation of other traders' information; hence the intersection of intervals. The key simplifications are that (a) there is no truncation, (b) the posterior distribution on the intersection of the n intervals is uniform, and (c) that the variance associated with intervals of varying width is roughly the variance associated with the expected width. The error due to (b) understates the true precision, while the error due to (c) overstates the true precision. Overall, the net error arising from these simplifications seems likely to be much smaller than the errors arising from subjects' varying abilities to infer other traders' private information from price.

Approximation (40) of σ_q ignores truncations and therefore breaks down when $w \approx 1$. Aggregating information by taking the intersection of private intervals doesn't work well in this case. (E.g., it can be shown that the intersection width $w_a \geq 2w - 1$.) Nor will it work well to take medians of individual traders' $\hat{m}$'s when most of them are truncated. Recall that $\hat{m} = \frac{w}{3}$ (or $1 - \frac{w}{3}$) when the interval is truncated at $m_L = 0$ (or at $m_U = 1$, i.e., at $m_L = 1 - w$). For signals with only two values, the median is a poor aggregator, since it is simply the majority value and ignores whether the majority is slender or overwhelming. For a slender majority, we should infer that m is close to 0.5 while for an overwhelming majority we should infer that it is closer to 0 (or 1) than to the median value $\frac{w}{3}$ (or $1 - \frac{w}{3}$).

The essence of the problem is that for w near 1, the signal is essentially binary — whether the revealed interval is truncated below at 0 or above at 1. These binary signals are generated by a Bernoulli process, and that insight provides well-oiled machinery for aggregation. We will now show that, if $m \in (1 - w, w)$, then the fraction μ of all truncations that are upper truncations approximates the true m.

Begin by recalling that $m_L = [m - \rho w]_0^{1-w}$, where $\rho \sim U[0, 1]$ and the upper and lower truncation points are attached to the right bracket. For any $w < 1$, the probability of a truncation at $m_L = 0$ is $p_L(m, w) = Pr[m \leq \rho w] = Pr[\rho \geq \frac{m}{w}] = 1 - \frac{m}{w}$ if $m < w$; otherwise $p_L = 0$. The probability of a truncation at $m_U = 1$ or $m_L = 1 - w$ is $p_U(m, w) = Pr[m - \rho w \geq 1 - w] = Pr[\rho \leq \frac{m+w-1}{w}]$ if $m > 1 - w$; otherwise $p_U = 0$. The probability of no truncation is the complement, $1 - p_L - p_U$. For $m \in [1 - w, w]$, that complement is $Pr[\rho \in [\frac{m-(1-w)}{w}, \frac{m}{w}]] = \frac{1-w}{w}$. See Figure A.8 for an illustration with $w = 0.7$ and a realization $m = 0.6 \in (.3, .7) = (1 - w, w)$. The fraction of the vertical line at $m = 0.6$ in the upper truncation zone $m_U = 1$ is $\frac{m+w-1}{w} = \frac{.6+.7-1}{.7} = \frac{3}{7}$, while the fraction in the lower truncation zone is $1 - \frac{m}{w} = \frac{1}{7}$.

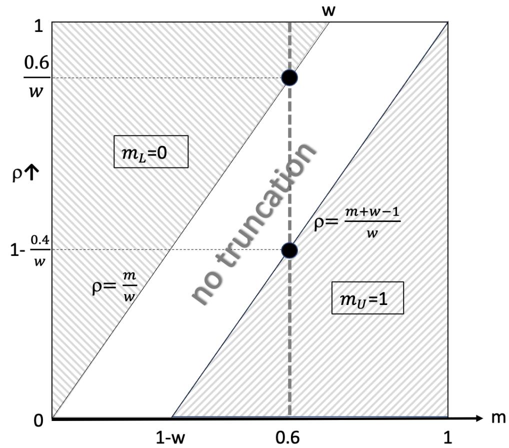
In general for $w \in (0.5, 1)$, a trader who sees a truncated interval will have an upper truncation $(1 = m_U \equiv m_L + w)$ iff the realization is positive of a Bernoulli trial with parameter $\mu = \frac{p_U}{p_U + p_L}$. The limiting expressions show that $\mu \approx m$ when $w \approx 1$: Taking the limit $w \to 1$, the probability of no truncation goes to 0, and $p_U \to m$ while $p_L \to 1 - m$. Hence the approximation $\mu = \frac{p_U}{p_U + p_L} = \frac{(m+w-1)/w}{(2w-1)/w} = \frac{m+w-1}{2w-1} \to m$ as $w \to 1$.[18] With $n \leq N$ traders getting independent trials with truncations, the fraction of upper truncations has the binomial distribution with parameter μ, i.e., has mean μ and variance $\frac{\mu(1-\mu)}{n}$. Since V scales m by factor g, we obtain $\sigma_q^2(N, w) \approx \frac{g^2 \mu(1-\mu)}{n} \approx \frac{g^2 m(1-m)}{N}$ for w near 1.0.[19]

In principle, the truncation zones illustrated in Figure A.8 could be used to derive, for any possible realization of N intervals for any fixed w, a maximum likelihood estimator for m, and its variance. That seems not worth the trouble for present purposes. Instead, our numerical calculations approximate $\sigma_q(N, w)$ given (m, w, N), by a weighted average of the truncation estimator and the previously derived estimator that ignores truncation. Specifically, the calculations combine (a) the estimate $g\sqrt{\frac{m(1-m)}{N}}$ with weight $p_L(m, w) + p_U(m, w)$, and (b) $\frac{gw}{\sqrt{3N}}$ with the complementary weight $(1 - p_L(m, w) - p_U(m, w))$.

[18] Although consistent, the estimator μ is biased and inefficient. A better estimator comes from solving the last expression for m, yielding $\tilde{m} = (2w - 1)\mu + 1 - w$.

[19] Texbooks sometimes suggest a "continuity correction" for binomial fractions. If there are $n \leq N$ upper truncations out of N trucations, set $\mu = \frac{n+0.5}{N+0.5}$ instead of $\frac{n}{N}$.

Figure A.8: Truncation zones in (m, ρ) space for $w = 0.7$.



Matlab Implementation. In order to solve a player's optimal w_o to maximize the objective function equation (4), we use grid search method in Matlab. First, we set $g = 0.7$ or 0.3, $k = 0.1$ or 2.5, the total number of players N on a grid of integers $N = 2, ..., 13$, both w and w_o on an equally spaced grid of 49 points from 0.0204 to 1, m and m_L on an equally spaced grid of 50 points from 0 to 1, and half spread s on an equally spread grid of 51 points from 0 to 3.

Then, we solve s using equation (35) given g, k, N, w_o, w. To calculate the RHS of equation (35), the subjective standard deviation about clearing price, σ_q, is weighted average of the just described untruncated σ_q and truncated σ_q. The function $H(s)$ is evaluated as $\frac{\phi(\frac{s}{\hat{\sigma}})}{1-\Phi(\frac{s}{\hat{\sigma}})}$ when $1 - \Phi(\frac{s}{\hat{\sigma}}) > e^{-15}$; otherwise $H(s) \approx s$ according to equation (36). A slight complication is that since the RHS of equation (35) depends on m via the truncated σ_q, the expectations is taken over m conditional on m_L according to equation (16). Hence in Matlab code, s becomes a function of m_L as well as the variables discussed earlier (g, k, N, w_o, w).

Finally, we use the grid search method to solve for a player's optimal w_o that maximizes the objective function equation (4), i.e., a player's best response of w_o to other players' w, given (g, k, N). Assuming q follows a truncated Normal distribution, the inner most integral of equation (4) is transformed as follows:

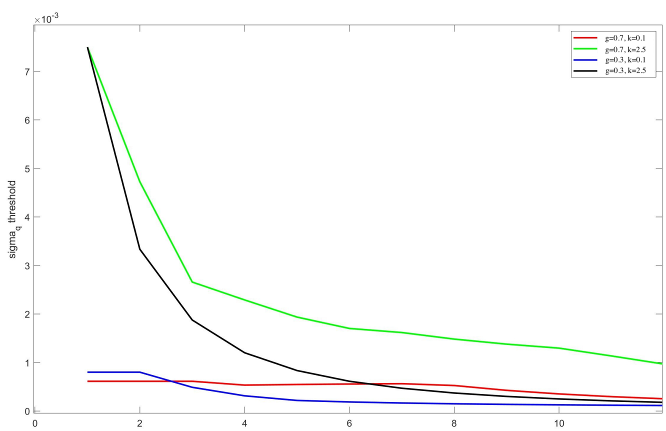
$$\int_0^{\hat{V}-s}[2(1-g+gm)-q]f(q)dq+\int_{\hat{V}-s}^{\hat{V}+s}(1-g+gm)f(q)dq+\int_{\hat{V}+s}^{1}qf(q)dq$$
$$=\int_1^{0}(1-g+gm)f(q)dq+\int_0^{\hat{V}-s}[(1-g+gm)-q]f(q)dq+\int_{\hat{V}+s}^{1}[q-(1-g+gm)]f(q)dq$$
$$=(1-g+gm)+\frac{\sigma_q}{Z\sqrt{2\pi}}\left\{e^{-\frac{[q-(1-g+gm)]^2}{2\sigma_q^2}}|_0^{\hat{V}-s}-e^{-\frac{[q-(1-g+gm)]^2}{2\sigma_q^2}}|_{\hat{V}+s}^{1}\right\} \tag{41}$$
$$where\ Z=\Phi(\frac{1-V(m)}{\sigma_q})-\Phi(\frac{0-V(m)}{\sigma_q}) \tag{42}$$

We calculate the outer two integrals taking into account of the truncated density $f(m|m_L)$ in equation (16) and the truncated distribution of m_L from equation (15).

The resulting best response of a trader's own w_o to other traders' w, given (g, k, N), is binary with w_o being either the lowest grid points (acquiring precise information) or the highest grid points (acquiring little information). When other traders' w is low (other traders have precise information), the trader's own optimal w_o is high (little information), and vice versa. This is illustrated in Figure A.7 in the text.

Whether a trader acquires lots of information or little information also depends on σ_q — how much information is reflected in prices. Figure A.9 shows, for different (g, k, N), σ_q (untruncated) thresholds, below which the trader chooses to acquire no information. That is, if the price conveys enough information (σ_q is small enough), then the trader does not have to acquire information him/herself since the acquisition is costly. As N increases, all else equal, σ_q thresholds decrease in some cases due to the faster increases in N than in the w threshold as $\sigma_q = \frac{gw}{\sqrt{3N}}$ is a function of both.

Figure A.9: Threshold w as a function of (g, k, N).



For different levels of g, all else equal, the σ_q thresholds are rather close to each other, as the effects from g and $w(g)$ thresholds (i.e., w rises as g decreases) cancel out with each other in the function of σ_q. As k increases, σ_q thresholds become higher. That is, when information becomes more costly, it is easier for a trader to forgo his/her own information acquisition even when the price does not convey as much information. $\square$

Appendix B Data Validation

This section provides summary statistics for the laboratory data and analysis to validate the experiment outcomes. But first, we summarize the key analysis results in this section in association with the theoretical predictions in Table 2 to give readers a sense of the experiment outcomes. In general, the information acquisition and price efficiency outcomes are consistent with our predictions, which also validates the efficiency of our experimental markets.

B.1 Information Acquisition

Table B.1 provides detailed summary statistics of the median width for each market and (g, k) group. The median width appears to increase with k and decrease with g.

To examine the distribution of chosen widths more closely, we plot Figure B.1. The first four bars break down the private information choices in all BDM rounds by k, g parameter settings. Recall from Figure 1 that w^*, the theoretical optimal choice, is a bit under 30 for $k = 0.1, g = 0.3$, and the first bar in Figure B.1 shows for that treatment that over 70% of subjects choose either midrange (30 or 50) or low range (1 or 10) values of w. The second bar shows a slight shift towards lower w choices when $k = 0.1, g = 0.7$, where the theoretical optimal choice is $w^* \approx 10$. The third bar shows a massive shift towards higher w choices for $k = 2.5, g = 0.3$ where $w^* = 100$. Finally, $w^* \approx 70$ when $k = 2.5, g = 0.7$, and the fourth bar indeed indicates a shift back towards lower (more informative) w choices.

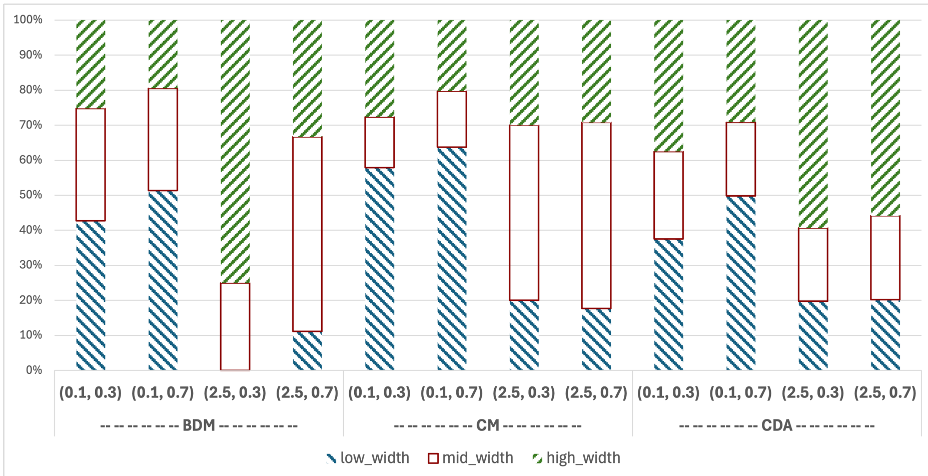
Table B.1: Summary Statistics of Information Acquisition: Median Width

	k=0.1,g=0.3	k=0.1,g=0.7	k=2.5,g=0.3	k=2.5,g=0.7
BDM	30	30	100	50
count	509	521	64	386
CM	10	10	50	30
count	297	308	84	381
CDA	50	30	70	70
count	374	394	152	392
Total	30	10	70	50
count	1180	1223	300	1159

The next four bars in Figure B.1 show the corresponding breakdown for all Call Market rounds. We see only fewer than 20% players choosing mid-range w's when information is cheaper ($k = 0.1$), much fewer than BDM markets. When information is more expensive ($k = 2.5$), more players chose middling and high width choices. The last four bars show the shares of the w choices in CDA sessions. Here we see more high width choices than in the other market formats. Across market formats, we can see that the shares of chosen mid-width are smaller in CM and CDA than in BDM, except for CM with high cost ($k = 2.5$).

This suggests that traders' choices in CM and CDA may be more polarized than in BDM, as in Prediction 1 (i).

Figure B.1: Mean Fractions of Width Choices



Notes: Low-width is $w_o < 30$ (i.e., 1 or 10, indicated by blue fine diagonal shading), mid-width is $w_o \in [30, 50]$ (i.e., 30 or 50, no shading), high-width is width $w_o > 50$ (i.e., 70 or 100, coarse green shading).

To examine more formally the impact of g, k, and competitivity on information acquisition, we use the following specification for all rounds t:

$$Info_t = \beta_0 + \beta_1 g_t + g_t Format_t' \boldsymbol{\beta}_2 + \beta_3 k_t + k_t Format_t' \boldsymbol{\beta}_4 + Format_t' \boldsymbol{\beta}_5 + \gamma_s + \epsilon_t \qquad (43)$$

where $Info$ is either the average of individual players' width choices w_o or else is the fraction of a specified width choices in round t. $Format$ is a matrix of dummy variables for Call Market and CDA Market, controlling for competitivity, and they interact with g and k. The baseline market is BDM. γ_s is fixed effect for each silo s. Recall that a silo is defined as the same group of players who form and participate in a particular market (BDM, CM, or CDA) for multiple rounds of our experiment. All regressions use OLS and robust standard errors unless otherwise specified.

Table B.2 reports fitted coefficient values and standard errors in regressions. In column (1), the dependent variable is average information acquisition per round w_o. The remaining columns of Table B.2 confirm corresponding shifts in the fractions of low (i.e., choosing widths 1 or 10), medium (i.e., choosing widths 30 to 50), and high width choices (i.e., choosing widths 70 or 100).

Consistent with Gu and Stangebye [2023] and our Proposition 1(ii)-(iii) and Prediction 1(ii), the average of traders' width choices across all market formats significantly decreases (i.e., purchased information precision increases) in default probability g (column (1)). More specifically, for every 10 percentage points increase in default risk, the average width for the baseline (i.e., BDM) is reduced by 1.25 (out of a maximum width of 100). Also consistent with our theory, the average of traders' width choices significantly increases in information cost k in all market formats. When k increases by 1, the average width in BDM will rise by 4.27. In addition, it appears in our experiments, the players' width choices in CM and CDA are less sensitive to g changes overall and more sensitive to k change at the lower and medium range of width choices (see Market interaction terms). Without BDM, we may underestimate default risk g's pure effect on individual information acquisition.

Table B.2: Information Acquisition by Round

	(1) w_o	(2) Fraclw	(3) Fracmw	(4) Frachw
Default Rate (g)	-0.125^{***}	0.240^{***}	0.068	-0.308^{***}
	(0.035)	(0.052)	(0.067)	(0.054)
Call Market × g	0.147^{***}	-0.219^{**}	0.041	0.178^{**}
	(0.038)	(0.086)	(0.091)	(0.075)
CDA × g	0.151^{***}	−0.099	−0.035	0.134^{*}
	(0.039)	(0.068)	(0.085)	(0.075)
Info Cost (k)	4.270^{***}	-15.360^{***}	7.452^{***}	7.910^{***}
	(0.677)	(0.888)	(1.166)	(1.026)
Call Market × k	-1.991^{**}	-4.815^{***}	7.110^{***}	-2.295^{*}
	(0.808)	(1.442)	(1.611)	(1.355)
CDA × k	−1.317	5.061^{***}	-5.912^{***}	0.851
	(0.972)	(1.178)	(1.571)	(1.382)
Call Market	-16.430^{***}	42.420^{***}	-21.550^{***}	-20.870^{***}
	(2.967)	(5.292)	(5.938)	(5.410)
CDA	-18.400^{***}	14.090^{***}	−7.129	−6.957
	(3.327)	(4.230)	(5.882)	(5.480)
Constant	12.810^{***}	32.000^{***}	25.070^{***}	42.930^{***}
	(2.757)	(3.227)	(4.769)	(4.504)
Obs.	427	427	427	427
R^2	0.409	0.748	0.494	0.613
test_cm_p			0.320	

Notes: Dependent variable in column (1) is the average of players' w_o choices each round. In columns (2)-(4), the dependent variables are fraclw, fracmw, and frachw (all in %), standing for the fractions each round of width choices of 1 or 10 (low), 30 or 50 (medium), and 70 or 100 (high), respectively. The benchmark market is BDM. The last row reports p-value for Wald test of the null hypotheses that the constant plus the CM dummy coefficient sum to 0. Baseline market is BDM. Silo fixed effects are included in all regressions. Robust standard errors are in parentheses. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Now we compare across three market formats and examine the impact of competitivity. The idea is that other traders' private information is irrelevant in the least competitive BDM market, but that information will be partially revealed under the more competitive market formats, reducing the incentive to purchase one's own private information. This also suggests that the impacts of g and k on w_o may be diminished but not reversed in the more competitive

CM and CDA markets. At last, the absence of symmetric pure strategy equilibrium in the competitive market formats, as in Prediction 1(i), leads to more polarized/asymmetric individual choices of w_o.

The significant and negative coefficients for dummy variables Call Market and CDA in columns (1) and their positive coeffients in column (2) of Table B.2 offer some evidence that the information acquisition is more in the more competitive markets (CM and CDA) than in the least competitive market (BDM) after controlling for default risk and acquisition cost. This is unexpected. However, this effect switches, i.e., more competitive markets acquire less information, when we use the player-round level data and control for player fixed effects. See Table B.3 column (2).

Table B.3: Width by Player & Round

	(1) Silo FE	(2) Player FE	(3) Quantile
g	-0.222^{***} (0.081)	-0.222^{*} (0.120)	-0.500^{***} (0.222)
Call Market × g	0.130 (0.100)	0.130 (0.121)	0.500^{**} (0.217)
CDA × g	0.087 (0.098)	0.092 (0.136)	0.500^{**} (0.235)
k	9.500^{***} (1.372)	9.500^{***} (2.289)	16.670^{***} (3.702)
Call Market × k	-0.030 (1.900)	-0.030 (3.080)	-8.333^{*} (4.200)
CDA × k	-1.987 (1.808)	-2.003 (2.369)	0.000 (5.719)
Call Market	-25.200^{***} (9.623)	10.330^{**} (4.054)	-34.170^{***} (6.358)
CDA	-9.184 (12.500)	27.150^{***} (4.550)	-15.000 (12.050)
Constant	49.680^{***} (6.177)	33.420^{***} (3.550)	43.330^{***} (6.294)
Obs.	3862	3862	3862
R^2	0.133	0.628	

Notes: Observations are at the level of individual-round. Column (1) has silo fixed effects and robust standard errors are clustered at the player level. Column (2) has player fixed effects and robust standard errors are clustered at the silo level. Column (3) uses quantile regression with bootstrapped standard errors. Baseline market is BDM. Robust standard errors are in parentheses. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

To examine the impact of market competitivity on the polarization of information choices, we focus on the fraction of medium width choices (i.e., choosing widths 30 to 50) from column (3) of Table B.2. This fraction can inform us how many players choose the middle ground and thus how concentrated the choices are at low or high width given a certain combination of g and k. On average, we can see that the fraction of medium-width choices in CM is much smaller than that in BDM (by 21.55%) after controlling for g and k. In fact, when we combine the constant (25.07%) with the dummy coefficients of Call Market (-21.55%) to calculate the average fraction of medium-width choices in CM and conduct the Wald test, the p-value (0.320) in the last row shows that the average fraction of medium-width choices in CM is not significantly different from zero. For CDA, the medium width fraction is also smaller than in BDM, although insignificantly (by 7.13%).

Moreover, comparing across columns, we can see that, for both CM and CDA markets, the fractions of medium width choices are significantly smaller than the fractions of their low width (column 2) and high width (column 4). All the above results suggest that, conditional on g and k, in CM (significantly) and CDA (insignificantly) markets, players are more split between the low and the high width choices than they are in BDM where more traders are choosing the medium widths (25.07%). Such evidence for more polarized width choices in at least CM than in BDM is consistent with the asymmetry prediction from Prediction 1(i).

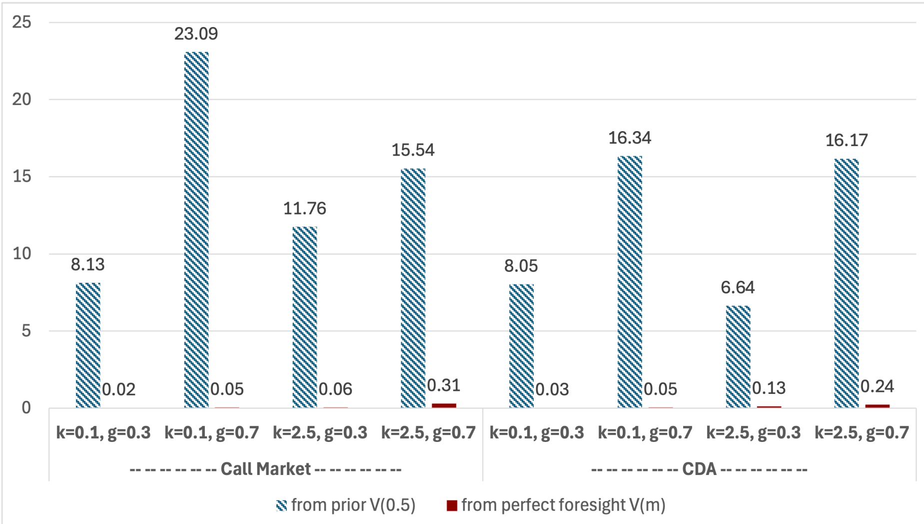
All the above results remain robust when we run the regressions at player and round level and use: (1) silo fixed effects, (2) player fixed effects, or (3) quantile estimator. Table B.3 columns (1)-(3) show the results. To summarize, we find that, consistent with our Proposition 1(ii)-(iii) and Prediction 1(ii), traders purchase more precise private information when it is cheaper (smaller k) and when the public information is ominous (i.e., high default probability g). Also consistent with Prediction 1(i), information purchase choices are more polarized/asymmetric across traders in more competitive markets. However, evidence is mixed for the impact of competitivity on information acquisition.

B.2 Information Aggregation and Price Efficiency

How much private information is potentially available in our competitive asset markets? There is an extensive literature that focuses on information aggregation in asset markets with exogenous private information; recent examples include Page and Siemroth [2017], Corgnet et al. [2020], and Albertazzi et al. [2021]. Although information aggregation *per se* is not our primary concern, it is an essential precursor of our main analyses of asset price volatility and liquidity and of the role of market formats. In that spirit, we now examine the empirical counterparts of fully aggregated imprecision w_a and bond value $V(m^*)$, as defined in Section 2.3.2, given traders' *endogenous* private information acquisition.

Figure B.2 shows the median absolute distance of fully aggregated bond value $V(m^*)$ (a) from no-information bond value V(0.5) with patterned bars, and (b) from perfect foresight $V(m)$ with red bars, for each (k, g) treatment in Call Markets and in CDA markets. In every case, the solid red bars are tiny, almost invisible, compared with the patterned blue bars. This shows that the fully aggregated bond value $V(m^*)$ typically tracks the perfect foresight value $V(m)$ quite closely, and suggests that the aggregate of traders' purchased private information is typically very precise. In addition, Table B.4 reports the median deviations of price from $V(m^*)$ for each combination of (k, g), which are small.

Figure B.2: Median Absolute Deviation of $V(m^*)$



Notes: $V(m^*) = 100(1-g) + gm^*$ is fully aggregated bond value. For each (k, g) treatment, the patterned blue bar (resp. the solid red bar) shows the median absolute deviation of $V(m^*)$ from prior bond value $V(0.5)$ (resp. from realized bond value $V(m)$).

Table B.4: Median Deviation of Clearing Price from V*

	k=0.1, g=0.3		k=0.1, g=0.7		k=2.5, g=0.3		k=2.5, g=0.7	
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
CM	0.72	1.03	-0.31	0.89	0.49	0.73	-0.85	3.13
CDA	-1.14	3.31	-2.54	6.08	-1.68	2.90	-0.71	7.00
Total	0.45	1.96	-1.07	1.97	-0.65	2.25	-0.85	4.08

Notes: Column (1) is the median market price minus V*, column (2) is the median absolute difference between market price and V*.

More formally, we examine the relation between bond price q and perfect foresight expected value $V(m)$ or fully aggregated bond value $V(m^*)$ under CM and CDA formats, using the regression specification

$$q_t = \beta V_t + \gamma_s + \epsilon_t, \tag{44}$$

where q_t is the market clearing price for CM or average transaction price for CDA in round t, and V is either $V(m)$ or $V(m^*)$. We include silo fixed effects (γ_s) to capture a possibly silo-dependent risk premium (since each silo s consists of a different set of human subjects) and use robust standard errors. If the price perfectly tracked the perfect foresight price $V(m)$ or the fully aggregated bond value $V(m^*)$, then the corresponding price response would be one-to-one, i.e., we would have $\beta = 1.0$.

Table B.5: Transaction Price by Round: CM and CDA

	(1) V=$V(m^*)$	(2) V=$V(m)$
V	0.843***	0.836***
	(0.0220)	(0.0235)
Obs.	267	267
R^2	0.870	0.865
test_p	< 0.001	< 0.001

Notes: Dependent variable is market clearing price each round for CM, and average transaction price each round for CDA. In the last row, test_p reports p-values for Wald tests of the null hypotheses that the coefficient of $V(m^*)$ in column (1) or of $V(m)$ in column (2) is equal to 1. All regressions include silo fixed effects. Robust standard errors are in parentheses. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table B.5 reports the results. The two columns confirm that transaction prices are highly correlated with both the perfect foresight price $V = V(m)$ and the fully aggregated price $V = V(m^*)$, with R-square of 0.87 and estimated β's of around 0.84. The last row of Table B.5 shows that these estimates are significantly below 1.0. Thus price movements include room for noise and perhaps bias. Indeed, Appendix B.3 Table B.7 shows that on average across all rounds, the fully aggregated bond value $V(m^*)$ is 2.68 (= average $\bar{e}$ in equation 11) above the average transaction price, suggesting small risk premium.

Now we examine the information aggregation and price efficiency in greater detail by including more explanatory variables in the regression by using only CM and CDA data. We run the following specifications 45 and 46 for information aggregation and price efficiency, respectively:

$$w_{at} = \beta_0 + \beta_1 g_t + \beta_2 g_t Format_t + \beta_3 k_t + \beta_4 k_t Format_t + \beta_5 Format_t + \beta_6 N_t + \gamma_s + \epsilon_t \quad (45)$$

$$\begin{aligned} q_t &= \beta_0 + \beta_1 V_t + \beta_2 V_t Format_t + \beta_3 V_t k_t + \beta_4 V_t g_t + \beta_5 V_t N_t \\ &\quad + \beta_6 Format_t + \beta_7 k_t + \beta_8 g_t + \beta_9 N_t + \gamma_s + \epsilon_t \end{aligned} \quad (46)$$

where, as in equation (9), w_a for each round t is the width of the intersection of realized intervals for recovery rate m. Price is q. Here $Format$ is a dummy variable for CDA only and the baseline format is CM. As usual, N is the number of traders in the market. We also include fixed effects (γ_s) and use robust standard errors.

Table B.6 column (1) reports the finding for specification 45. As pointed out in Prediction 1(v), fully aggregated information is more precise (smaller width w_a) when cost k is smaller. But we find no significant effect from the content of the public information g. This is not a surprising result given the result in Table B.2 column (1): individual own width choices react less to g in the CM and CDA than in BDM. Also, unexpectedly, the coefficient of size N is significantly positive, which means that the aggregate information reduces when there are more players the aggregate information. This indicates a stronger indirect effect of N on chosen widths than its direct effect on w_a and a strong free-riding force.

Table B.6: Information Aggregation by Round: CM and CDA

	(1)	(2)	(3)
	w_a	q	q
		$[V = V(m^*)]$	$[V = V(m)]$
V		0.576***	0.567***
		(0.127)	(0.126)
V × CDA		−0.261***	−0.261***
		(0.050)	(0.051)
V × k		−0.034**	−0.040**
		(0.016)	(0.017)
V × g		0.002	0.002
		(0.001)	(0.001)
V × N		0.026**	0.027**
		(0.011)	(0.011)
CDA	4.310*	17.950***	17.260***
	(2.226)	(4.867)	(5.000)
Info Cost (k)	2.279***	2.076	2.352*
	(0.441)	(1.288)	(1.343)
CDA × k	0.674	0.488	0.792
	(0.827)	(0.601)	(0.611)
Default Rate (g)	0.022	−0.232**	−0.229**
	(0.015)	(0.109)	(0.110)
CDA × g	0.004	−0.159***	−0.153***
	(0.023)	0.036	0.036
Size (N)	6.284***	−7.452***	−7.635***
	(1.741)	(1.963)	(1.974)
Constant	−66.460***	94.730***	96.290***
	(17.450)	(20.510)	(20.550)
Obs.	267	267	267
R^2	0.313	0.913	0.911

Notes: Dependent variable for Column (1) $w_a = \min m_{Ui} - \max m_{Li}$ for each round is the width of the intersection of realized intervals for recovery rate m. Dependent variable for both columns (2) and (3) is market clearing price each round for CM, and the average transaction price each round for CDA. The explanatory variable V in column (2) is fully aggregated expected value $V(m^*)$, while in column (3) it is perfect foresight expected value $V(m)$. Size is the number of traders in the market. Baseline format is CM. All regressions include silo fixed effects. Robust standard errors are in parentheses. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Columns (2) and (3) in Table B.6 report the results for specification (46) to examine price efficiency. Consistent with Prediction 1(iv), the negative interaction coefficient for $V \times k$

and the positive coefficient for $V \times N$ suggest that price q indeed better reflects available information and true value when private information is cheaper and when there are more traders. The coefficient for the default rate interaction $V \times g$ is again insignificant but has the predicted positive sign.[20]

As for the impact of market competitivity on information aggregation and price efficiency, recall there are two opposing effects. On one hand, free riding incentivizes each trader to purchase less precise information in a more competitive market. On the other hand, we expect the increased interaction in a more competitive market to better aggregate whatever information is present. In column (1) of Table B.6, we can see that the CDA dummy coefficient is positive and significant (4.310), indicating that a more competitive market (here CDA) incentivizes less individual acquisition of private information, which leads to less aggregated information in the market. This result suggests that the information free-riding force dominates the effect of increased interaction in a competitive market.

In column (2) of Table B.6, the coefficient of $V(m^*)$'s interaction term with the CDA dummy (-0.261) suggests that prices better reflect aggregate information in the moderately competitive format CM than in the most competitive CDA. In column (3), the parallel interaction coefficient of $V(m)$ with CDA is also statistically significant, at -0.261, indicating that prices track true value more closely also in the baseline (moderately competitive) CM format than in CDA. These results suggest that competitivity reduces price efficiency, and are consistent with that in column (1) where we find competitivity reduces information aggregation. In summary, we find that, consistent with Prediction 1(iv) and (v), information aggregation and price efficiency reduce with information cost k and market competitivity, and the former decreases while the latter increases with the number N of traders. But there is no significant effect from the content of the public information g.

Overall, the bond's perfect foresight value $V(m)$, fully aggregated value $V(m^*)$, and market price q are highly correlated with each other in CM and CDA markets. Asset price is close but not equal to $V(m)$ and $V(m^*)$ on average, since in most treatments there is a small positive risk premium. These results underscore the generally high efficiency of our experimental markets and help to validate our laboratory data.

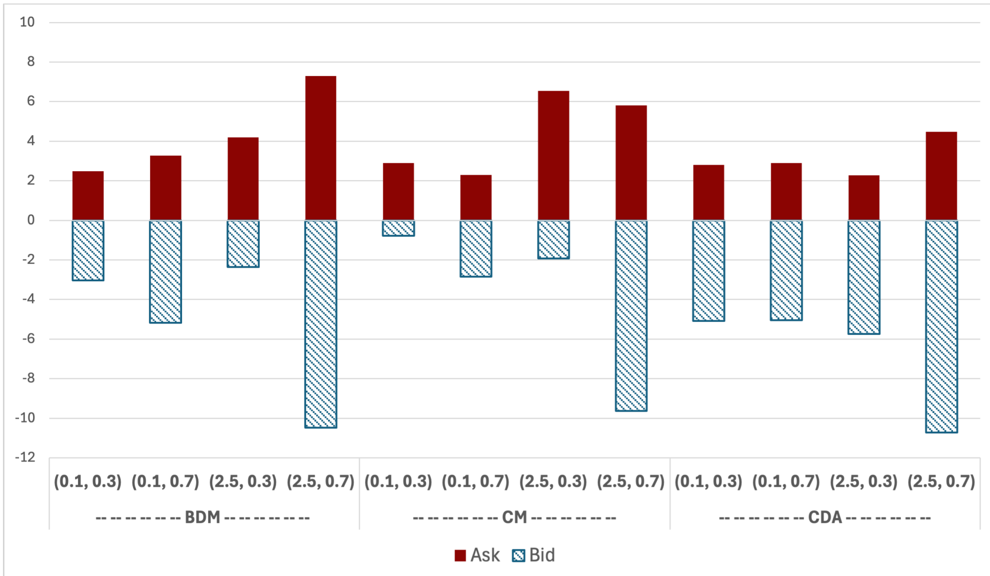
B.3 Risk Premium

Coming back to the topic of risk premium, we examine it more closely at the level of traders as well as of markets. Figure B.3 shows that, at the level of individual trader, median asks are above $V(m^*)$ (solid red bars) and median bids are below $V(m^*)$ (patterned bars) for every market format and every (k, g) treatment. In most (but not all) cases, the patterned

[20] The point estimates of $V \times g$ coefficient in both columns, 0.002 and 0.002, are not economically trivial. It suggests that, when public information conveys an ominous instead of benign state (so g rises by $70 - 30 = 40$), the impact of a change (Δ) in V on price is boosted from 0.5Δ in the baseline to about 0.6Δ. That is, a more ominous public information weakly increases information aggregation and price efficiency.

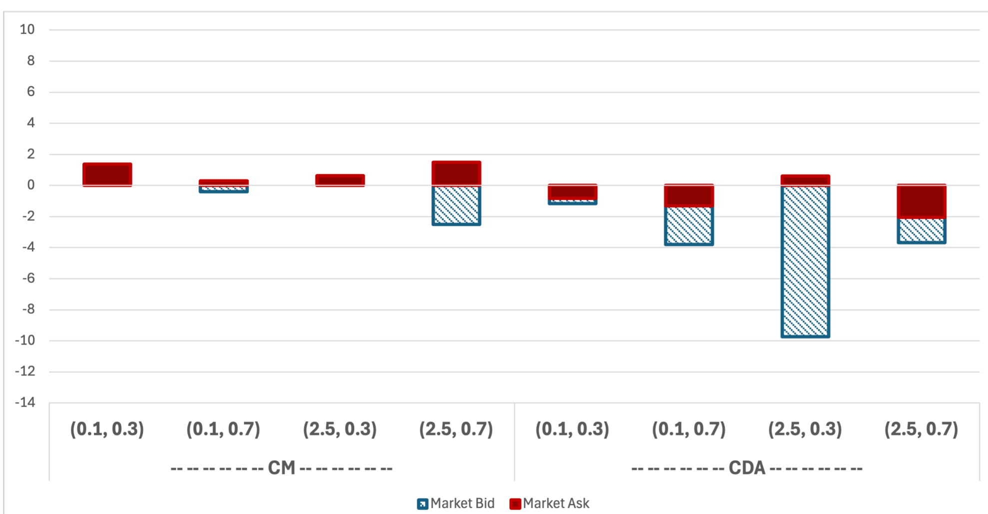
bars are longer than the solid red bars, i.e., the median bid is further away from $V(m^*)$ than is the median ask, again suggesting a small but positive risk premium.

Figure B.3: Median deviation of individual traders' bids and asks from $V(m^*)$



Notes: For each (k, g) treatment in each market format, the blue bar is the median of individual (bid minus V^*) and the red bar is the median of individual (ask minus V^*).

Figure B.4: Median deviation of market bids and asks from $V(m^*)$



Notes: For each (k,g) treatment in each market format, the blue bar is the median of market [bid minus $V(m^*)$] and the red bar is the median of market [ask minus $V(m^*)$]. CDA market exhibits a higher risk premium than CM (also see in Table B.7).

The comparison with the corresponding market-level deviations (Figure B.4) is also instructive. The market ask in CM is the lowest rejected ask among all traders and the market bid is the highest rejected bid. Of course, at any point in time in the CDA, the market ask is the best (lowest) ask and the market bid is the best (highest) bid; unless otherwise stated, we report time averages by round. Figure B.4 shows the distance between $V(m^*)$ and market bid (patterned bars) or market ask (red bars). In CDA treatments, the market ask either is below $V(m^*)$ or else has a smaller positive deviation from it than the market bid's negative deviation, in either case consistent with a positive risk premium. In CM treatments the market bid and ask deviations are mostly smaller than CDA. The result that CDA market has a more positive risk premium than CM is consistent with the result in Table B.6 that prices in CDA market are slightly less responsive to changes in $V(m^*)$ on average.

In addition, Table B.7 shows that on average across all rounds, the fully aggregated bond value $V(m^*)$ is 2.68 (= average $\bar{e}$ in equation 11) above the average transaction price, suggesting small risk premium. Also note that CDA market's risk premium is about the same as BDM market's and both are larger than CM's, consistent with Figure B.4.

Table B.7: Risk Premium and Deviations

	$\bar{e}$	d	ϵ
BDM mean	-3.48	0.02	-0.00
Observations	160	160	1480
CM mean	-0.70	-0.25	-0.00
Observations	122	122	1070
CDA mean	-3.47	0.16	-0.00
Observations	145	145	897
Total mean	-2.68	-0.01	-0.00
Observations	427	427	3447

Notes: $\bar{e}$ is calculated as the average of $(q - V^*)$ for each round. d is calculated as $(V^* - V(m))$ for each round. ϵ is calculated as $(q - V^* - \bar{e})$ across all player-round in BDM and CM and all transaction-round in CDA. In BDM and CM, q is measured as the midpoint of bid and ask by each player in each round. In CDA, q is actual transaction price.

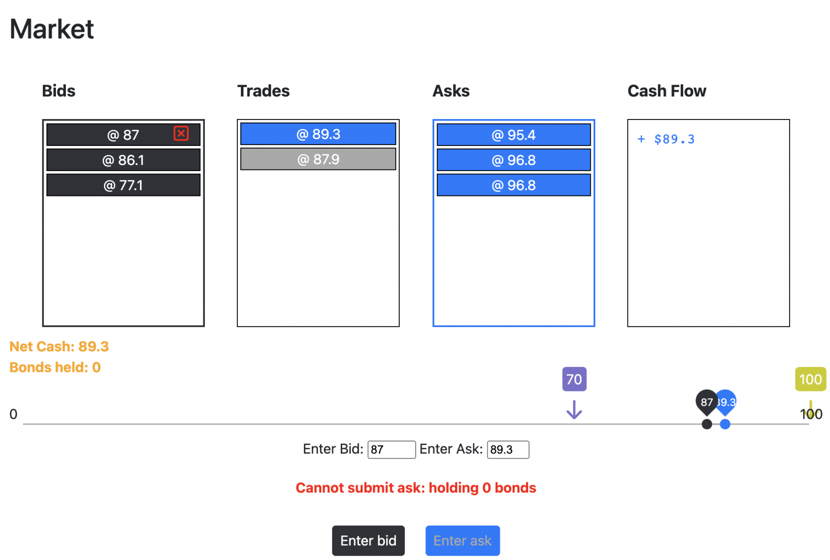
At last, we assume that the risk premium $-\bar{e}$ is constant in the main text and it is reassuring that w_a is insignificant in affecting the premium's changes. But we do see that default risk increases while competitivity reduces the risk premium volatility (see Table C.3).

Appendix C Supplementary Figures and Tables

C.1 CDA Experiment Screen

Figure C.1 shows one trader's CDA screen in our experiment. Using the keyboard or dragging the black dot on the price line, the trader has just entered a bid of 87. That bid can be immediately cancelled by clicking the red x in the Bids box, which shows two other traders' (lower) bids. Earlier in the current round the trader had entered (via the keyboard or the blue dot) an ask of 89.3. A transaction resulted (as noted in the Trades box) when some other trader entered a higher bid, resulting in a cash inflow of +89.3 and a holding of 0 bonds by this trader.

Figure C.1: CDA Trading Platform



C.2 Volatility

Table C.1: Volatility

	(1) k=0.1,g=0.3	(2) k=0.1,g=0.7	(3) k=2.5,g=0.3	(4) k=2.5,g=0.7
Between-Round Volatility σ_r^2	77.40	454.10	82.41	346.51
Observations	132	136	32	127
Within-Round Volatility σ_e	114.94	123.28	78.39	132.04
Overall Volatility σ_q	186.96	577.94	124.52	442.18
Observations	1051	1084	248	1064

Notes: Between-round volatility reports the variance of $[V^* - V(0.5)]$ (at the transaction level) for each group. Within-round volatility reports the variance of $\epsilon = q - V^* - \bar{e}$ across all player-round in BDM and CM and all transaction-round in CDA for each group. In BDM and CM, q is measured as the midpoint of bid and ask by each player in each round. In CDA, q is actual transaction price.Overall volatility reports the variance of $[q - V(0.5) - \bar{e}]$ across all player-round in BDM and CM and all transaction-round in CDA for each group. In BDM and CM, q is measured as the midpoint of bid and ask by each player in each round. In CDA, q is actual transaction price.

Table C.2: Robustness: Price Volatility Regression Results at the Player-Round Level

	Between-round σ_r^2		Within-round σ_e^2		Overall σ_q^2	
	(1)	(2)	(3)	(4)	(5)	(6)
Aggr. Width (w_a)	−0.694					
	(1.918)					
Call Market × w_a	−5.828					
	(5.576)					
CDA × w_a	−2.328					
	(3.039)					
Own Width (w_o)			3.078***		−2.294***	
			(0.379)		(0.430)	
Call Market × w_o			−2.175***		−2.219***	
			(0.461)		(0.648)	
CDA × w_o			−3.061***		2.368***	
			(0.402)		(0.518)	
Default Rate (g)	8.161***	8.259***	0.255	−1.340**	8.177***	11.470***
	(0.922)	(0.932)	(0.430)	(0.594)	(0.641)	(1.345)
Call Market × g	0.485	0.776	0.216	1.294	1.033	1.598
	(1.561)	(1.566)	(0.602)	(0.885)	(1.023)	(1.927)
CDA × g	−0.167	−0.465	0.107	1.682***	−0.061	−3.280**
	(1.405)	(1.365)	(0.497)	(0.646)	(0.786)	(1.419)
Fraclw		1.662		0.267		−1.801
		(1.240)		(0.532)		(1.955)
Call Market × fraclw		0.379		−1.285		−1.673
		(1.633)		(0.890)		(2.570)
CDA × fraclw		−0.722		−0.623		2.990
		(1.986)		(0.613)		(2.075)
Call Market	−84.480	−155.400	244.500***	194.200***	−40.020	176.900
	(91.780)	(118.900)	(51.410)	(59.630)	(83.550)	(172.600)
CDA	50.890	80.060	176.800***	20.33	−244.300***	−146.600
	(87.090)	(110.900)	(42.680)	(34.100)	(55.670)	(131.500)
Constant	−149.900**	−204.800***	−185.100***	−22.600	28.060	−166.200
	(65.050)	(56.730)	(46.950)	(49.340)	(80.250)	(174.300)
Obs.	427	427	3575	2014	3575	2014
R^2	0.258	0.265	0.106	0.047	0.154	0.195

Notes: Dependent variable σ_r^2 is the squared deviation of $V(m^*)$ from $V(0.5) = E(V(m^*))$ in each round, and $\sigma_e^2 = \varepsilon^2$ is the squared deviation of price from $(V(m^*) + \bar{e})$, while σ_q^2 is the squared deviation of price from $(V(0.5) + \bar{e})$, where $-\bar{e} = -Ee$ is the empirical risk premium. Aggregate width w_a and individual own width w_o are defined in Section 2. Fraclw in each round is the percentage of traders choosing the narrowest widths (1 or 10). For BDM and CM, q is calculated as the midpoint of bid and ask by each player each round. For CDA, q is the average of actual transaction prices per player each round if there exists any transaction, and missing otherwise. When we impute the missing transaction prices for a player-round in the CDA using time-weighted or unweighted bids and asks and their midpoint, the results remain similar. Note the observation numbers here are higher than those in Table 4 because we count each transaction twice by including both makers' and takers' transaction prices for the player-round level regressions whereas in Table 4 we only count each transaction once. $V(m^*)$, $V(0.5)$ and $\bar{e}$ are calculated at the round level. The baseline market is BDM. Silo fixed effects are included in all regressions. Robust standard errors are in parentheses. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table C.3: Risk Premium Volatility by Round

	(1)	(2)	(3)	(4)
w_a	-0.026		-0.026	
	(0.816)		(0.816)	
Call Market $\times$ w_a	-0.641		0.068	
	(1.376)		(1.844)	
CDA $\times$ w_a	-0.224		-0.224	
	(2.445)		(2.445)	
g	0.808^{**}	0.788^{**}	0.808^{**}	0.788^{**}
	(0.321)	(0.307)	(0.321)	(0.307)
Call Market $\times$ g	-0.258	-0.451	0.207	0.141
	(0.444)	(0.387)	(0.492)	(0.478)
CDA $\times$ g	1.175	1.174	1.175	1.174
	(0.782)	(0.732)	(0.782)	(0.732)
Fraclw		-0.533^{*}		-0.533^{*}
		(0.303)		(0.303)
Call Market $\times$ fraclw		0.142		0.325
		(0.347)		(0.400)
CDA $\times$ fraclw		0.403		0.403
		(0.908)		(0.908)
Call Market	-30.640	-14.070	-53.070^{*}	-52.170
	(28.810)	(26.440)	(30.910)	(35.260)
CDA	-112.200^{***}	-120.800^{**}	-112.200^{***}	-120.800^{**}
	(43.170)	(48.690)	(43.170)	(48.690)
Constant	34.520	48.620^{***}	34.520	48.620^{***}
	(24.080)	(18.070)	(24.080)	(18.070)
Obs.	427	427	427	427
R^2	0.179	0.183	0.160	0.163

Notes: The dependent variable is the squared deviation of $E(q - V^*)$ for each round from their mean. Columns (1) and (2) uses clearing price in the volatility calculations for CM. Columns (3) and (4) uses round average of the midpoints between bid and ask pairs in the volatility calculations for CM. Baseline market is BDM. Silo fixed effects are included in all regressions. Robust standard errors are in parentheses. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

C.3 Spreads

Table C.4: Summary Statistics of Individual Spread

	k=0.1,g=0.3			k=0.1,g=0.7		
	Initial	Ending	Mean	Initial	Ending	Mean
Mean	14.93	12.69	13.57	17.46	13.98	15.41
St.dev.	20.50	19.66	19.52	21.35	18.99	19.01
Median	7.60	5.40	6.70	10.00	7.00	8.60
Count	1061	1061	1061	1106	1106	1106
Observations	1061			1106		
	k=2.5,g=0.3			k=2.5,g=0.7		
	Initial	Ending	Mean	Initial	Ending	Mean
Mean	12.27	10.07	10.92	22.30	17.27	19.30
St.dev.	17.82	17.18	15.95	21.30	19.09	18.38
Median	8.10	6.40	7.64	17.20	13.60	15.10
Count	263	263	263	1059	1059	1059
Observations	263			1059		

Notes: In CDA markets, initial (resp. ending) individual spread is individual's first ask minus first bid (resp. last ask minus last bid) in each round, and mean spread is the average ask minus average bid. Individuals who do not place at least one ask as well as at least one bid are omitted from further analysis of individual spread. In BDM and CM, the three measures of individual spread coincide and no individuals are omitted.

Table C.5: Summary Statistics of Market Spread by Round

	(1) k=0.1,g=0.3	(2) k=0.1,g=0.7	(3) k=2.5,g=0.3	(4) k=2.5,g=0.7
Call Market				
mean	1.88	2.86	1.00	5.49
sd	2.03	4.24	1.31	4.93
median	1.00	1.50	0.50	4.00
count	35	36	8	43
CDA				
mean	5.69	7.89	3.13	9.01
sd	6.34	10.28	3.18	9.21
median	3.57	4.36	1.55	5.42
count	43	44	16	42
Total				
mean	3.98	5.63	2.42	7.23
sd	5.23	8.47	2.86	7.53
median	2.00	2.00	1.40	5.00
count	78	80	24	85

Notes: Market spread for CM is the lowest rejected ask minus the highest rejected bid in each round; market spread for CDA is average of the lowest ask available minus the highest bid available in the market calculated in each second within a round.

C.4 Trading Volume

Trading volume is a secondary indicator for liquidity and may be of interest in its own right. Although our theoretical framework has little to say about trading volume, some previous empirical and theoretical studies suggest that it is negatively related to bid-ask spread. For instance, He and Wang [1995] examines trading volume's reactions to information flows. This subsection provides further evidence from our laboratory experiment.

Using the same specification as in the spread regressions, we replace spread measures with trading volume that is defined as the total number of trades.[21] Table C.6 column (1) shows the results at the level of player and round. In CM (baseline), when a player chooses a higher width (less private information), the number of trades s/he carries out tends to decrease (less liquid). An interpretation is that, from Table 7 we can see that with more precise private information (smaller w_o), a trader will more aggressively narrow his/her spread, and thus s/he can make more trades. Moreover, here the harmonic mean of other players' widths (w_{hm}) has little impact on trading volume. In CDA, however, the impact of a player's own width choice w_o on trading volume is closer to zero. These findings are also consistent with the results in Table 7 in the sense that w_o negatively affects liquidity.

Table C.6: Trading Volume: CM & CDA

	(1) Individual	(2) Market
Own Width (w_o)	-0.001^{***} (0.000)	
CDA × w_o	0.001^{***} (0.000)	
Harmonic Mean of Others' Widths (w_{hm})	-0.002 (0.001)	
CDA × w_{hm}	0.002 (0.001)	
Aggr. Width (w_a)		-0.031^{***} (0.009)
CDA × w_a		0.031^{***} (0.009)
Default Rate (g)	0.001 (0.001)	0.006^{*} (0.003)
CDA × g	-0.001 (0.001)	-0.006^{*} (0.003)
CDA	-0.523^{***} (0.055)	-2.400^{***} (0.248)
Constant	0.523^{***} (0.055)	2.400^{***} (0.248)
Obs.	2382	267
R^2	0.388	0.875

Notes: The dependent variable is the number of trades by player and round in column (1) and is the total number of trades by round in column (2). Aggregate width w_a and individual own width w_o are defined as in the theory section. w_{hm} is the harmonic mean of other players' widths (i.e., excluding a player's own width w_o). Call Market is the baseline. Silo fixed effects are included in all regressions. Robust standard errors are in parentheses. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

[21] We ignore the variable *Size* in trading volume regressions because including it does not change our estimates and *Size*'s own coefficient is virtually zero.

Table C.6 column (2) analyzes trading volume at the market level, i.e., by round. Aggregate width has a negative effect on trading volume in CM but no effect in CDA. These results may reconcile the conflicting theoretical results in papers such as Pfleiderer [1984] and Varian [1985], which each examines the effects of private information and/or the market's aggregation of information on trading volume. In particular, while Varian [1985] argues that investors' different opinions cause trades, Pfleiderer [1984] predicts that when price does not fully reveal aggregate information, expected trading volume decreases with the disagreement between investors, as investors take large positions based on their own private information.

This is consistent with our results in CM: As aggregate width gets larger, there is more disagreement between players, and thus they trade less. Meanwhile, CDA market allows easier learning of others' private information and better information revelation through prices, where private information becomes less useful than in the CM. A larger aggregate width in CDA market allows more speculative gains and thus increases trade as in Varian [1985] and He and Wang [1995]. For future research, it would be interesting to develop a comprehensive theoretical framework to rationalize our trading volume findings.

In addition, we notice that the coefficients for the CDA dummy are negative and significant in both columns (1) and (2) of Table C.6, which implies that market competitivity appears to significantly decrease trading volumes and thus both individual and market liquidity. This result is consistent with our prior findings in Section 4.3 that competitivity reduces liquidity. Overall, the trading volume results are consistent with our liquidity results using spreads.

Instructions

Welcome, and thank you for participating in this experiment. From now until the end of the experiment, please turn off your cell phone and do not communicate with other participants. If you have any questions, please raise your hand; an experimenter will come to answer your question. Please pay careful attention to the instructions as real money is at stake. You are guaranteed a show up fee of $5.00 but can earn considerably more.

The Basic Idea

In this experiment, you will be buying and/or selling bonds, which are promises to pay a certain amount at the end of each round. If the bond does not default (i.e., the promise is kept) then you will be paid 100 game credits for each bond you hold when the trading round ends. If the bond defaults (promise is not fulfilled in that round), then you will be paid a smaller amount, between 0 and 100. You will be able to purchase private information about what that smaller amount will be.

At the end of the round, your payoff is your payments on the bonds you hold, plus revenue from any bonds you sold, minus the cost of any bonds you bought, minus the cost of any private information that you decide to buy. Your payoffs are accumulated over all rounds minus a participation fee in each block and converted into US dollars at an announced rate; that is your take-home pay. The maximum pay (rarely achieved) is US$35.00.

Bond Value

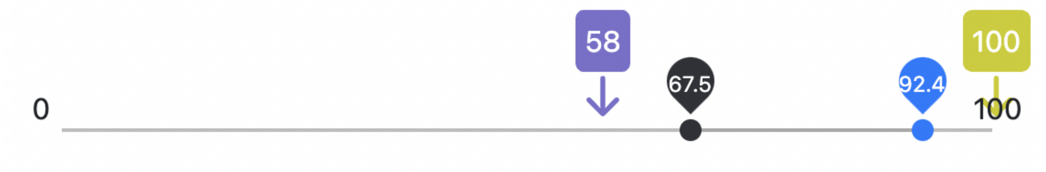
You will be told the probability g of bond default at the beginning of each round. If you purchase private information, you will learn mL, the lowest possible bond payment in default, and also the highest possible bond payment in default, mH. The lowest (resp. highest) expected bond value is 100 times the non-default probability (1-g), plus mL (resp. mH) times the default probability g. In the example below, with g = 70%, mL = 40 and mH = 100, we see that the lowest expected bond value is 58.00 and the highest is 100.00.

Lowest expected bond value: 30% * 100 + 70% * 40 = 58

Highest expected bond value: 30% * 100 + 70% * 100 = 100

How to Trade

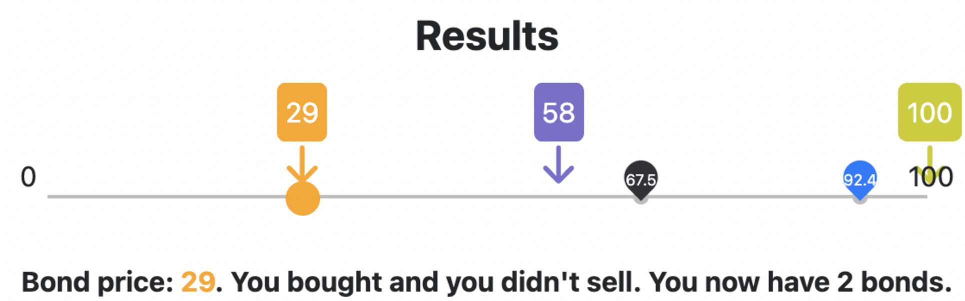
After purchasing private information (as explained below), you will be able to buy and/or sell bonds using sliders. You click and drag the black ball just above the price line to set your **bid** --- the highest price at which you are willing to **buy** a bond. Likewise, you click and drag the blue ball to set your **ask** --- the lowest price at which you are willing to **sell** a bond. The purple marker is the lowest expected bond value; probably you will want to bid at least that much. The yellow marker is the highest expected bond value; probably you will not want to ask more than that. In the example below, the player set her bid at 67.5 and her ask at 92.4.



Bond price and transactions

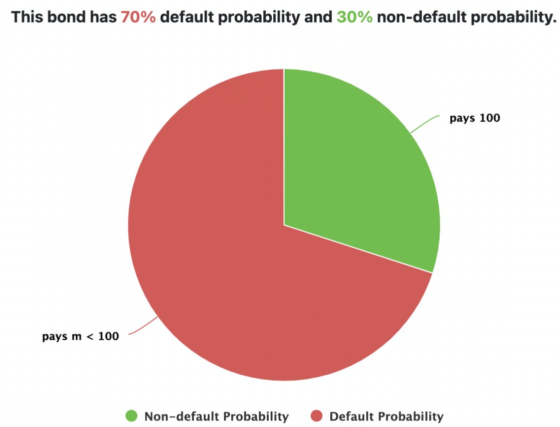
In this experiment, you are matched with an automated trader who picks a random price between 0 and 100. This is shown as a yellow ball that bounces back and forth and stops at a random point on the price line. If your bid is higher than that random price, then you will buy a bond from the automated trader. If your ask is lower than that random price, then you will sell a bond.

For example, if you bid 67.5 and asked 92.4, then there would be no trade if the yellow ball stopped at 70 (or at any other price between 67.5 and 92.4). If the yellow ball instead stopped 95, then you would sell a bond at that price – your credit balance would go up by 95 and you would no longer have the bond. Likewise for any other price above 92.4. On the other hand, if the yellow ball stopped below 67.5, then you would buy at that lower price. For example, if the yellow ball stopped at 29, then you would buy one bond (in addition to the one you already have) and your credit balance would decrease by 29.



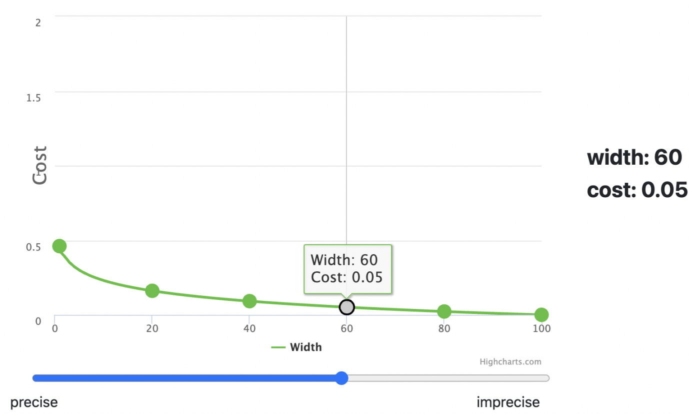
Information about bonds: public

At the very beginning of each period, you receive free public information about the bond's default probability. For example, in the following graph, the probability of default is represented in the red area of the pie chart as 70%, while the probability of non-default is 30%. In other words, you have a 30% chance of receiving 100 and 70% chance of receiving a smaller amount ranging from 0 to 100 for each bond you hold at the end of that period.



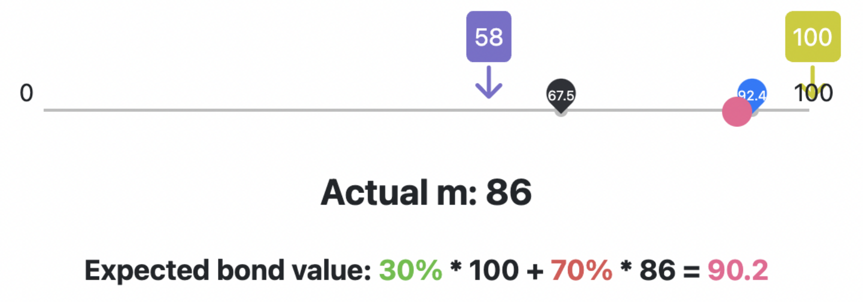
Information about bonds: private

What is that smaller payment m if the bond defaults? You know that it is between 0 and 100, but you can narrow down that range [mL, mH] by purchasing private information. Slide the blue tab to the left to narrow the range (and increase the cost you pay for the information), and slide it to the right to widen the range of uncertainty (but reduce the cost of information). In the example below, the player has chosen to pay 0.05 to learn the value of m within a range of width 60. The true value of m has already been determined, and the following screen will report mL and mH = mL +60, with the true m equally likely to be anywhere in between when mL>=0 and mH<=100.



Determining bond payments

After you have seen the public information on bond default probability and bought private information on bond payment in default, you then set your bid and ask prices for bonds, as already explained. Next, the system reveals the actual value m of the default bond payment, and the true expected bond value. In the example below, m turns out to be 86 and the expected bond value is 90.2.



Finally, the system determines whether or not the bond defaults that period. If non-default, each bond you still hold will pay 100; otherwise, it will pay the amount m, which was 86 in the example.

Your payoff

The final payoff of each round will be the credits left after bond trade (payments on bonds held plus income from bonds sold minus cost of bonds bought), plus payments of the bond(s), minus the cost you pay for bond information. In the example below, the player with one initial bond paid 0.05 for private information and bought one more bond at price of 29 (bid higher than 29). <u>If the bond defaults</u>, with 2 bonds (each has a value of 86) on hand minus the payment for the second bond, the player's payoff will be 86*2-29-0.05=142.95. On the other hand, <u>if the bond does not default</u>, then the player will have a payoff of 2*100-29-0.05=170.95.

Recap

First, given public information on default probability, you will choose how much to pay for more precise information on the defaulted bond payment. Then you set bid and ask prices, and may buy or sell a bond. Finally, you see whether or not bonds default this period, and if so, what they pay. Your payoff is higher each period when you buy a bond at a lower price than its actual payment, and when you sell a bond at a higher price than the bond's actual payment.

Instructions

Welcome, and thank you for participating in this experiment. From now until the end of the experiment, please turn off your cell phone and do not communicate with other participants. If you have any questions, please raise your hand; an experimenter will answer your question. Please pay careful attention to the instructions as real money is at stake. You are guaranteed a show up fee of $5.00 but can earn considerably more.

The Basic Idea

In this experiment, you will be buying and/or selling bonds, which are promises to pay a certain amount at the end of each round. If the bond does not default (i.e., the promise is kept) then you will be paid 100 for each bond you hold when the trading round ends. If the bond defaults (promise is not fulfilled in that round), then you will be paid a smaller amount, between 0 and 100. You will be able to purchase private information about what that smaller amount will be.

At the end of the round, your payoff is the payments on the bonds you hold, plus revenue from any bonds you sold, minus the cost of any bonds you bought, minus the cost of any private information that you decide to purchase. Your payoffs are accumulated over all rounds minus a participation fee in each block and converted into US dollars at an announced rate; that is your take-home pay. The maximum pay (rarely achieved) is US$35.00.

Bond Value

You will be told the probability of bond default at the beginning of each round. If you purchase private information, you will learn mL, the lowest possible bond payment in default, and also the highest possible bond payment in default, mH. The lowest (resp. highest) expected bond value is 100 times the non-default probability, plus mL (resp. mH) times the default probability. For example, suppose that the default probability = 70%, mL = 0 and mH = 60, then:

Lowest expected bond value: 30% * 100 + 70% * 0 = **30**

Highest expected bond value: 30% * 100 + 70% * 60 = **72**

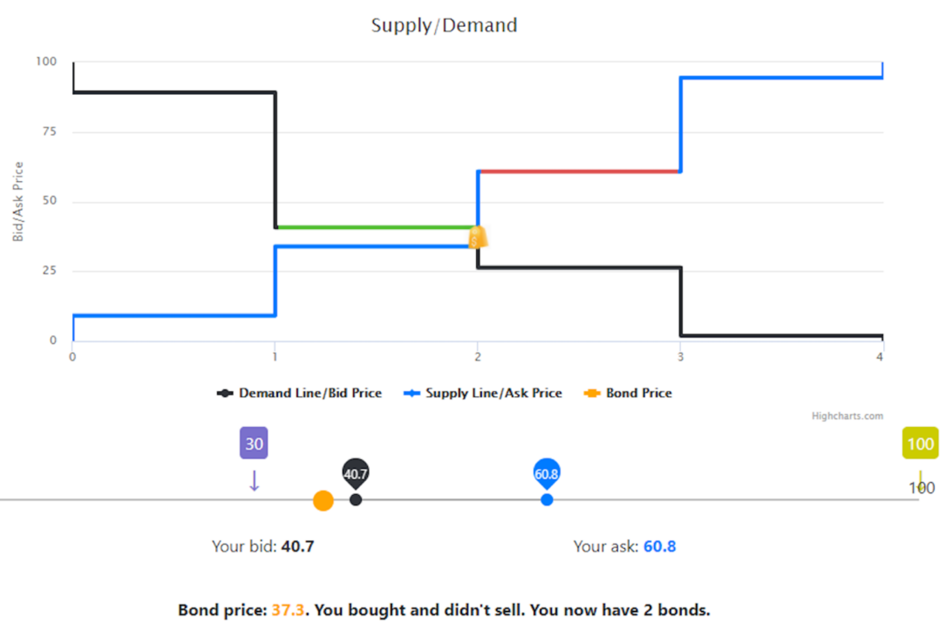
How to Trade

After purchasing private information (as explained below), you will be able to buy and/or sell bonds using sliders. You click and drag the black ball just above the price line to set your **bid** --- the highest price at which you are willing to **buy** a bond. Likewise, you click and drag the blue ball to set your **ask** --- the lowest price at which you are willing to **sell** a bond. The purple marker is the lowest expected bond value; probably you will want to bid at least that much. The yellow marker is the highest expected bond value; probably you will not want to ask more than that. In the example below, the player set her bid at 40.7 and her ask at 60.8.

Bond price and transactions

Your bid and ask, and the bids and asks of the other bond traders, are submitted to an auction market that determines the bond price as follows. The bids, sorted from highest price to lowest, are the demand schedule; and the asks, sorted from lowest to highest, are the supply schedule. A bond price is found where the schedules cross and so the number of bonds bought equals the number sold. That bond price is the height of the yellow marker on the supply-demand graph and it is also shown as a yellow ball on the horizontal price line. If your bid is higher than that bond price, then you buy a bond, and if your ask is lower than that bond price then you sell a bond.

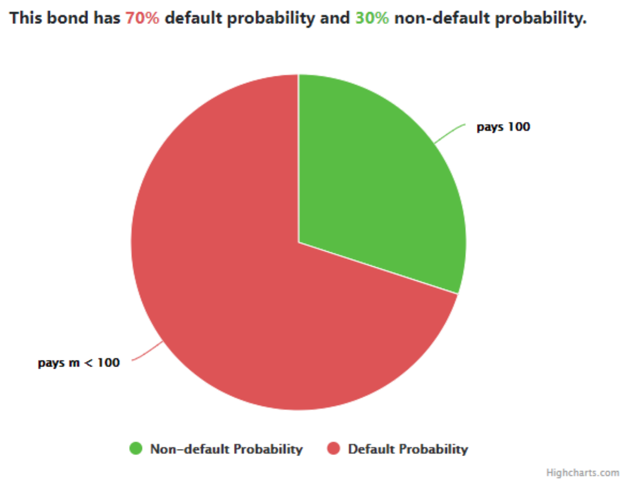
For example, if you bid 40.7 and asked 60.8, then there would be no trade if the bond price set at auction turned out to be 50 (or at any other price between 40.7 and 60.8). If the bond price turned out to 65, then you would sell a bond at that price – your cash balance would go up by 65 and you would no longer have the bond. Likewise, for any bond price above 60.8. On the other hand, if the bond price is below your bid of 40.7, then you would buy at that lower price. For example, bond price turns out to be 40, then you would buy one bond (in addition to the one you already have) and your cash balance would decrease by 40. In the Figure below, the bond price is 37.3, and you buy and didn't sell a bond at that price.



While for another bond trader in the market who bid 35 and asked 50, he/she won't be able to buy or sell the bond and his/her cash balance does not change.

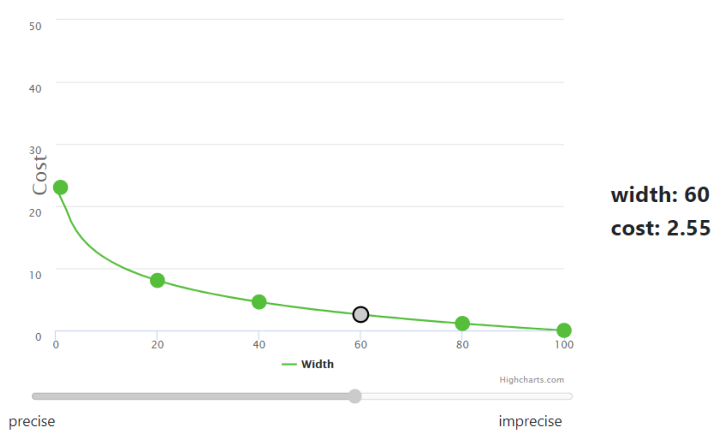
Information about bonds: public

At the very beginning of each period, you receive free public information about the bond's default probability. In the graph below, the probability of default (shown in red) is 70%, while the probability of non-default (in green) is 30%. In this case, for each bond you hold at the end of the period, you have a 30% chance of receiving the full value of 100, and 70% chance of receiving some smaller amount m.



Information about bonds: private

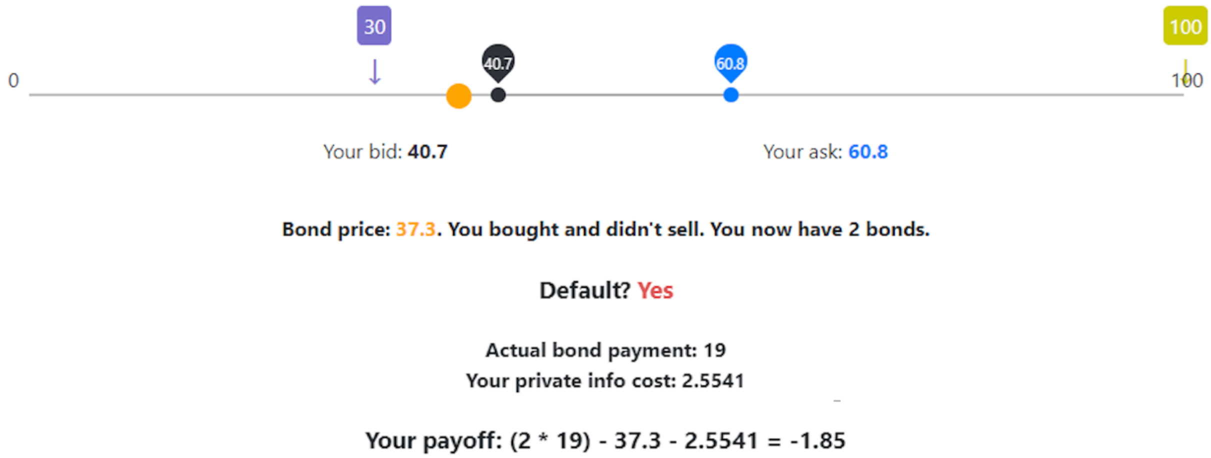
What is that smaller payment m if the bond defaults? You know that it is between 0 and 100, but you can narrow down that range [mL, mH] by purchasing private information. **Select one of the six precision options on the graph. The leftmost point is the narrowest range of information with the highest cost, and as you move to the right points, you have a wider range of information with lower cost.** In the example below, the player has chosen to pay 2.55 to learn the value of m within a range of width 60. The true value of m is already determined, and the next screen will report mL and mH = mL + 60, with the true m equally likely to be anywhere in between when mL>0 and mH<100.



Determining bond payments

After you have seen the public information on bond default probability and bought private information on bond payment in default, you then set your bid and ask prices for bonds, as already explained.

Finally, the system determines whether or not the bond defaults that period. If non-default, each bond you hold will pay 100; otherwise, it will pay the amount m, which is between mL and mH.



Your payoff

The final payoff of each round will be receipts from bonds sold minus cost of bonds bought, plus the payments on bonds you hold, minus the cost you pay for bond information. Suppose that you paid 2.55 for private information and bought a bond for 37.3 and did not sell your other bond, and that m = 19. If the bond <u>does not default</u>, your payoff will be 100 + 100 – 37.3 – 2.55 = 160.15. On the other hand, <u>if the bond defaults</u> your payoff will be 19 + 19 – 37.3 – 2.55 = -1.85.

Recap

First, given public information on default probability, you will choose how much to pay for more precise information on the defaulted bond payment. Then you set bid and ask prices, and may buy or sell a bond. Finally, you see whether or not bonds default this period, and if so, what they pay. Your payoff is higher each period when you buy a bond at a lower price than its actual payment, and when you sell a bond at a higher price than the bond's actual payment.

Instructions

Welcome, and thank you for participating in this experiment. From now until the end of the experiment, please turn off your cell phone and do not communicate with other participants. If you have any questions, please raise your hand; an experimenter will answer your question. Please pay careful attention to the instructions as real money is at stake. You are guaranteed a show up fee of $5.00 but can earn considerably more.

The Basic Idea

In this experiment, you and the other participants will be buying and/or selling bonds. A bond promises to pay a certain amount to the participants at the end of each round. If the bond does not default (i.e., the promise is kept) then you will be paid 100 for each bond you hold when the trading round ends. If the bond defaults (promise is not fulfilled in that round), then you will be paid a smaller amount, between 0 and 100. You will be able to purchase private information about what that smaller amount will be.

At the end of the round, your payoff is the payment on the bonds you hold, plus revenue from any bonds you sold, minus the cost of any bonds you bought, minus the cost of any private information that you decide to purchase. Your payoffs accumulate over all rounds; after subtracting given participation fees, they will be converted into US dollars at an announced rate; that is your take-home pay. The maximum pay (rarely achieved) is US$35.00.

Bond Value

You will be told the probability of bond default at the beginning of each round. If you purchase private information, you will learn mL, the lowest possible bond payment in default, and also the highest possible bond payment in default, mH. The lowest (resp. highest) expected bond value is 100 times the non-default probability, plus mL (resp. mH) times the default probability. E.g., with mL = 0, mH = 100 and default probability = 20% (so non-default probability is 80%) the lowest and highest expected bond values are calculated as follows.

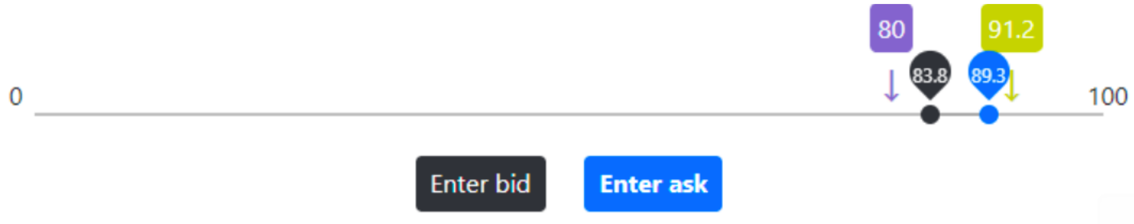
Your private information about m: 0 ≤ m ≤ 100

Lowest expected bond value: 80% * 100 + 20% * 0 = **80**

Highest expected bond value: 80% * 100 + 20% * 100 = **100**

How to Trade

After purchasing private information (as explained below), you will be able to set your buying or selling price using sliders. You click and drag the black ball just above the price line and then **click the Enter bid button** to set your **bid** --- the highest price at which you are willing to **buy** a bond. Likewise, you click and drag the blue ball and then **click the Enter ask button** to set your **ask** --- the lowest price at which you are willing to **sell** a bond. The purple marker is the lowest expected bond value. The yellow marker is the highest expected bond value. In the example below, the player has currently set her bid at 83.8 and her ask at 89.3.



Instead of dragging the black and blue balls, you can also enter specific numbers in provided boxes to slide the balls and specify your bids and asks. But **always click the Enter bid/ask buttons to submit your bids/asks**.

You can freely adjust your bid or ask whenever you want during the trading period, but you can only set one bid and one ask at a time. If you enter a second bid (or second ask), it will automatically replace your current bid (or ask).

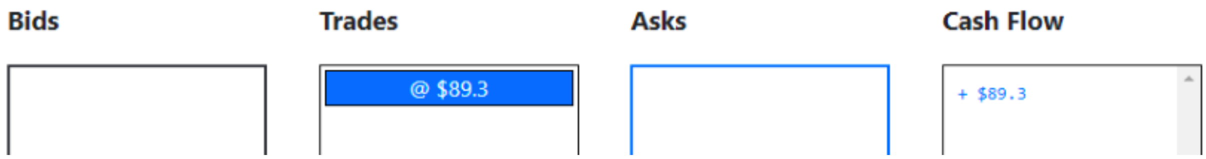
Bond price and transactions

Your bid and ask, and the bids and asks of the other bond traders, are entered into an auction market that you can view in the text boxes. The bids, sorted from highest price to lowest, are listed in the leftmost, black-framed text box; and the asks, sorted from lowest to highest, are listed in blue-framed text box on the right.

If you enter a new bid that is higher than lowest listed ask, then you buy a bond at that ask price; otherwise, your bid enters the sorted list of bids and is marked on your screen by a red check box. Likewise, if you enter a new ask that is lower than the highest listed bid, then you sell a bond at the listed bid price; if it is higher than the highest listed bid then your ask enters the sorted list and is marked by a red check box. You can quickly cancel your listed bid or ask by clicking the check box. The middle box shows the prices of all trades so far; your own trades are marked in black if you bought the bond, and in blue if you sold. Trades that are grey are others' transactions. The text box on the far right shows the impact on your cash flow.

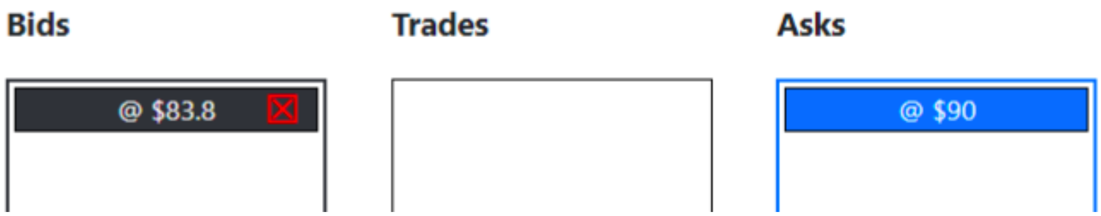
For example, suppose that you entered an ask at 89.3 when the highest bid is 87, as in the illustration below. Then your ask goes into the list (at the top if no other listed ask is lower).

If another trader enters a bid at a higher price, say 91, then you would sell her your bond at your listed ask price. Your cash flow would be +89.3 and you would no longer have the bond.

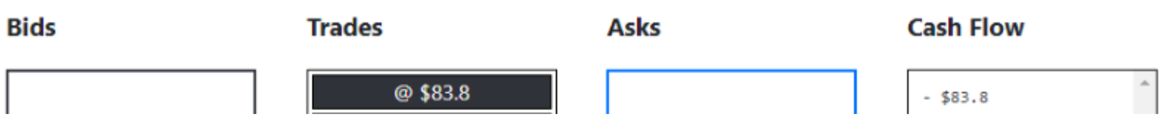


Meanwhile, her cash flow would be -89.3 and she would hold one more bond.

Likewise, if you set your bid price to 83.8 when the lowest ask from other participants is 90 it will enter the Bids list:



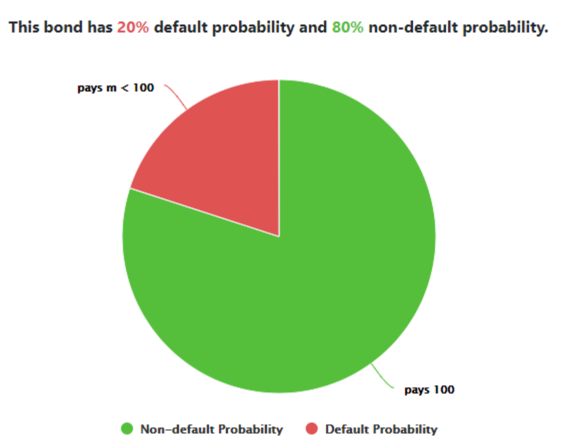
Later, if you bid remains at the top of the list and someone enters an ask lower than 83.8, then you would buy a bond at your bid price – your total assets would go up by 1 bond and your cash balance will decrease by 83.8.



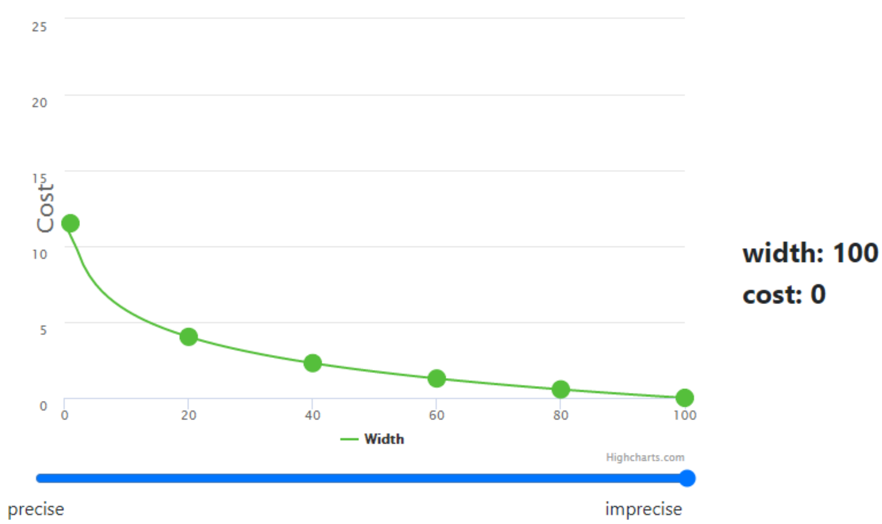
You can hold anywhere from 0 to 2 bonds during each round. You can also double click on another player's existing bid or ask to sell or buy a bond.

Information about bonds: public

At the very beginning of each period, you receive free public information about the bond's default probability. In the graph below, the probability of default (shown in red) is 20%, while the probability of non-default (in green) is 80%. In this case, for each bond you hold at the end of the period, you have a 80% chance of receiving the full value of 100, and 20% chance of receiving some smaller amount m.



Information about bonds: private
What is that smaller payment m if the bond defaults? You know that it is between 0 and 100, but you can narrow down that range [mL, mH] by purchasing private information. **Select one of the six precision options on the graph. The leftmost point is the narrowest range of information with the highest cost, and as you move to the right points, you have a wider range of information with lower cost.** In the example below, the player has chosen to pay 0 to learn the value of m within a range of width 100. The true value of m is already determined, and the next screen will report mL and mH = mL + 100, with the true m equally likely to be anywhere in between when mL>0 and mH<100.



Determining bond payments
After you have seen the public information on bond default probability and bought private information on bond payment in default, you then enter and adjust your bid and ask prices and trade bonds, as already explained.

When the trading period is over, the system determines whether or not the bonds default that period. If non-default, each bond you hold will pay 100; otherwise, it will pay the amount m, which is between mL and mH. In example below, the bond did not default and pay m = 100.

Your bonds did not default.
Actual held bond payment: 100
Your private info cost: 0

Your payoff
The final payoff for a round will be net cash flow (i.e., receipts from bonds sold minus cost of bonds bought), plus the payments on bonds you hold, minus the cost you pay for bond

information. In the example above, you sold one bond for 89.3 then you bought a bond for 83.8, producing a net cash flow of 89.3 - 83.8 = 5.5. Moreover, since you started with one bond, sold it and then bought bond, your final bond holding is 1. Since the bond did not default, with a bond payment of 100, your payoff for this period will be 5.5 + (1 * 100) - 0 = $105.5.

If the bond defaulted with actual m=50, you would have received a bond payment of $50 and your payoff would have been (89.3 – 83.8) + (50*1) - 0 = 55.5.

Recap

First, given public information on default probability, you will choose how much to pay for more precise information on the defaulted bond payment. Then you set bid and ask prices, and may buy/sell bonds. Finally, you see whether or not bonds default this period, and if so, what they pay. Your payoff is higher each period when you buy a bond at a lower price than its actual payment, and when you sell a bond at a higher price than the bond's actual payment.