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Stress tests and information disclosure: An experimental analysis

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ABSTRACT

To improve the stability of the banking system the Dodd-Frank Act mandates that central banks conduct periodic evaluations of banks' financial conditions. An intensely debated aspect of these 'stress tests' regards how much of that information generated by stress tests should be disclosed to financial markets. This paper uses an environment constructed from a model by Goldstein and Leitner (2018) to gain some behavioral insight into the policy tradeoffs associated with disclosure. Experimental results indicate that variations in disclosure conditions are sensitive to overbidding for bank assets. Absent overbidding, however, optimal disclosure robustly improves risk sharing even when banks behave non-optimally.

1. Introduction

Since the passage of the Securities Exchange Act in 1934 the disclosure of information regarding the financial condition of firms has been a centerpiece of financial market regulation. Over time, disclosure requirements have been refined and reinforced with regulations such as the Sarbanes-Oxley Act (2002), which was intended to improve the accuracy and reliability of corporate disclosures, and more recently the Dodd-Frank Act (2010) which among other things, mandates that central banks conduct periodic 'stress tests' that evaluate a financial institution's capacity to respond to conditions of extreme stress. A key issue that has been the subject of intense debate among economists and policymakers regards the degree and precision with which the information collected by regulators should be disclosed publicly.

On an intuitive level, the case for disclosure is strong. The provision of otherwise unavailable information allows traders to impound that information into bids and asks, in this way allowing prices to more fully reflect the underlying value of a firm's equity.[1] This intuition, however, does not carry over to 'second best' environments, characterized by informational asymmetries. A voluminous theoretical literature, summarized in Goldstein and Yang (2017), analyzes a variety of ways excessive information disclosures may create inefficiencies. One classic concern about disclosure is based on the 'Hirshleifer effect' (Hirshleifer, 1971). The idea is that excessive disclosure of a bank's condition might undermine the valuable lending activities that interbank markets promote. Banks are subject to random liquidity shocks. Interbank loan markets allow banks with cash deficiencies to borrow funds from banks with excess cash, in the process rationalizing liquidity across regions and sectors of an economy, and expanding the amount of lending a banking system can support.[2] The public disclosure of information about the capacity of individual banks to withstand such shocks could critically limit these lending opportunities. Importantly, the potentially undesirable effects of information disclosure on banks extends to contexts broader than the interbank market. In money markets, for example, bank asset valuations by fund

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[1] This intuition was first formalized by Blackwell (1951), who showed that in a rational expectations environment, the provision of additional information about the underlying state of an economy at least weakly improves market efficiency.

[2] An extensive theoretical literature studies the risk sharing activities in interbank markets (e.g., Allen and Gale 2004a, 2004b). Davis et al. (2019, 2020) report a pair of experiments conducted to evaluate the efficiency and stability of interbank trade.

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managers may also be negatively impacted by excessive information disclosures.[3]

An implication of this logic is that information disclosure can have important downsides. As Goldstein and Leitner (2018) observe, however, the possible negative consequences of disclosures about a bank's financial condition must be balanced against potentially critical desirable effects. In the 2009 financial crisis, for example, interbank markets 'locked up,' and it was only with the provision of some information about bank solvency that interbank trade resumed. A more complete position, argue Goldstein and Leitner, is that regulators balance the costs and benefits of disclosure, and then disclose an optimal amount of information about banks.

Goldstein and Leitner develop an elegant model that identifies the impacts of variations in disclosure frequencies on risk sharing activity. This paper reports an experiment that uses a simple variant of their analysis to shed some light on conditions under which disclosure may improve or undermine socially desirable risk pooling. Our experimental design consists of groups of four participants, a bank and three buyers, who make decisions over a sequence of repeated stationary periods. In each period, the bank is endowed with an asset, the value of which equals the sum of a *basic value* reflecting the bank's asset type, and an *idiosyncratic risk,* modelled as a uniformly distributed random dividend with a zero mean. Buyers make bids to acquire the asset in light of information provided about the asset's expected value, which may reflect a pooling of basic value realizations, depending on the treatment. Subsequently, the bank decides to either sell the asset to the highest bidder or to hold the asset to maturity.

The driving feature of the analysis is that the bank receives a bonus if it either sells the asset at a price above a cutoff value, or holds the asset and the value at maturity exceeds the cutoff. This sort of payoff discontinuity is a common feature of the models of financial fragility, first studied by Diamond and Dybvig (1983). In these models, banks take short-term deposits to invest in illiquid long-term projects which yield 'bonuses' in the form of an investment return if the projects mature. In the case of unexpectedly high levels of early deposit withdrawals (e.g., a 'bank run'), a bank becomes financially stressed and must consider selling some of its illiquid long-term projects to recover needed liquidity.

The bonus cutoff creates a nonlinearity in a bank's payoff function. For a range of expected values below the bonus cutoff, the risk neutral bank will hold the asset to maturity rather than sell at prices equal to the asset's expected value, in hopes that the asset's value at maturity exceeds the cutoff. For a range of expected values above the cutoff, the bank will sell the asset at prices below its expected value if the bid exceeds the bonus cutoff, since doing so will guarantee the bonus. [4]

In this framework, a regulator's decision regarding the pooling of bank asset types can affect bonus incidences, or the frequency with which banks can hold on to their illiquid assets. Specifically, a combination of basic values that exceed the bonus cutoff with basic values that fall below it can generate a pooled asset with an expected value that still exceeds the bonus cutoff, in this way allowing some banks that would otherwise be unable to realize the bonus with certainty to do so. Such a 'partial' pooling of basic value information can increase the incidence of bonuses relative either to a case where buyers are provided with full information about the basic value of each asset, or a case where buyers are provided with no information about the expected value of assets, if the expected value of all assets combined falls below the bonus cutoff. In this context, information pooling is a sort of risk pooling, and increases the incidences of bonus realizations. Goldstein and Leitner equate this notion to curbing bankruptcies.

The primary objective of this experiment is to behaviorally examine bank asset sales decisions under different degrees of information pooling. Optimal sales decisions in this context requires that banks essentially act as though risk preferring when the asset's expected value falls below the bonus cutoff (since in this case a sale would guarantee that the bonus would not be realized), and as risk averse when the asset's expected value exceeds the bonus cutoff (since in this second case a sale below the asset's expected value would still guarantee realization of the bonus). We would be unsurprised to find that at least some banks focus more on the asset's expected value than the receipt of the bonus. We aim to examine whether such a bias exists, and if it does, how it affects the predicted benefits of partial information pooling.

A lesser, secondary objective of our experiment is to study the behavioral potential for overbidding in a context where buyers have exactly the same, albeit uncertain, information about the value of an asset. To elicit asset prices, Goldstein and Leitner appeal to predictions from a simple posted-bid auction structure. Given uncertainty about the asset's final value, this structure closely parallels a common-value auction setup, where overbidding has frequently been observed, but with the critical difference that buyers possess no private information on which to base their bids. For this reason, our experiment allows us to study the individual characteristics that motivate overbidding.

Importantly, the posted-bid structure is not crucial to the Goldstein and Leitner analysis, and other auction formats may generate bids closer to an asset's expected value. For that reason, in addition to sessions with real buyers, we conduct a parallel series of sessions where buyer bids are simulated and, in each instance, equal the asset's expected value.

In brief overview, our experimental results indicate that in treatments with human asset buyers, the buyers persistently overbid for bank assets, even in this limiting context where the expected value of the asset is the same for all bidders. Analysis of individual bidding decisions suggests that the overbidding is driven by bidders placing too much weight on the asset's idiosyncratic component, raising bids when the last previous realization was high. The persistent overbidding undermines the effects of disclosure rule variations.

Environments characterized by overbidding for bank assets, however, are unlikely to be a primary concern among regulators worried about bank insolvencies in naturally-occurring contexts. In treatments with automated buyers, we find that banks deviate substantially from risk-neutral actions, with many banks focusing on the asset's expected value, exclusive of the bonus. Nevertheless, 'optimal' disclosure increases risk sharing largely as predicted, despite deviations of banks' sales decisions from risk-neutral actions. We regard the resilience of improved risk-sharing under optimal disclosure to behavioral deviations as lending powerful support to the model's behavioral relevance.

[3] Several related theoretical papers examine dimensions of the Hirshleifer effect that extend beyond the interbank market. Dang et al. (2017) examines conditions under which keeping loan information secret allows banks to produce safe liquidity. Alvarez and Barlevy (2015) considers a model in which the disclosure of balance sheet information can limit the capacity of banks to raise equity. They show that in the case that disclosure negatively affects new equity sales, required disclosures can improve welfare only when the potential for contagion in banking system is sufficiently high. Monnet and Quintin (2017) examines an information design problem in which investors choose to incentivize managers to withhold some information they might receive about the value of their investments in a bank in order to preserve the bank's liquidity in secondary markets.

[4] If the expected value of the asset makes the probability of realizing the bonus 0, the risk neutral bank will demand no premium above the expected value to sell the asset. If the expected value of the asset makes the probability of realizing the bonus certain, the bank will refuse to sell the asset for anything below its expected value. For other expected values of the asset, the bank has a minimum acceptable price which generally differs from the asset's expected value. We demonstrate this relationship for our particular experimental design in Fig. 1.

Before proceeding, we stress the importance of using laboratory methods in this context. Experiments have frequently been used as an aid to theory in exploring the potential effectiveness of policy options.[5] As Falk and Heckman (2009) observe, laboratory methods offer two key advantages over other methods for assessing the effects of new policies: data can be easily and inexpensively collected, and policy variations can be exogenously modified in a controlled manner, thereby allowing causal inference.

It is true that the subjects in laboratory markets (usually a convenience sample of undergraduate students) are typically less sophisticated than the actors in the pertinent natural contexts. Nevertheless, the laboratory environment, constructed on the domain of a theory, is far simpler than the pertinent natural context, and actions are less subject to ancillary considerations.[6] Observing behavior in the laboratory that is consistent with the predictions of a theoretical model lends support to the use of that model for policy purposes in the sense that the theory can be expected to generate the predicted effects as long as the theory's assumptions effectively capture the dominant drivers of behavior in the natural context. On the other hand, the failure of a theory to organize behavior in the laboratory casts doubt on the theory's policy relevance, and suggests that a different (or improved) theory merits consideration.

The use of experiments to explore new regulations in banking and financial markets is no exception to the growing application of laboratory methods to study policy questions. In the last decade, an experimental literature studying policies affecting financial fragility and policy responses to the financial crisis has emerged, offering useful insights into and qualifications of new financial regulations.[7]

Within the experimental financial market literature, this paper contributes to the study of contexts where information disclosure might create inefficiencies. Related papers include Cornand and Hieneman (2014), who report an experiment that evaluates the Morris and Shin (2002) 'beauty contest' model. In this model, public forecasts bias prices because sellers respond strategically to the anticipated effect of the public signal on the actions of other sellers. Experimental results suggest that when the distribution of rationality levels among traders approaches anything resembling that observed in natural contexts, the response to public information is insufficiently large to distort prices.[8] In another contribution, Enke and Zimmermann, 2019 study a behaviorally more promising 'correlation neglect' phenomenon, or a failure of agents to adjust for the common source of a public signal when forming value estimates. They find that correlation neglect may prominently bias private estimates and thus prices. A final pertinent paper, Ruiz-Buforn et al. (2021), studies an asset market in which traders are presented with common public signals. The authors find that traders frequently overrespond to public signals, a result they attribute to the effects of public signals on traders' second order beliefs, as studied by Allen et al. (2006). To the best of our knowledge, no previous experimental work investigates the Hirshleifer effect. The present investigation represents an initial attempt to address this gap in the literature.

We organize our presentation in the following way. Section 2 presents our implementation of the Goldstein and Leitner model, behavioral conjectures, and procedures of our experiment. Section 3 presents results and discussion. Our concluding comments appear in Section 4.

2. The experimental environment, hypotheses, and procedures

2.1. Experiment design

Goldstein and Leitner study a context in which risk neutral banks seek funding for an asset of uncertain value from potential buyers.[9] We present here a simplified version of this model articulated in terms of our experiment parameter choices. The behavioral relevance of the model turns on the conformity of agent decisions with assumed actions and on the predicted consequences of agent interactions. We formalize these assumed individual actions and predicted group interactions as a series of hypotheses which we state as we proceed through the development.

The environment consists of a bank and competitive buyers who make decisions over a series of periods in a competitive market where information releases are mediated by a regulator. At the outset of each period the bank is endowed with an asset, which yields a stochastic return that is the sum of two components, a basic value, or bank 'type' θ, drawn with equal likelihood from $\{\$6,\ \$9, \$13\}$, and a random dividend $\varepsilon \sim U[-\$5,\ \$5]$, which represents the bank's idiosyncratic risk. Basic value and dividend distributions are related to all agents as common knowledge. Depending on the treatment, however, the bank and buyers may have different information about asset value realizations. Neither the bank nor buyers know the random dividend when decisions are made, but in some treatments banks are better informed about the asset's basic value realization.

2.1.1. Buyers

Risk neutral, competitive buyers bid for assets via a standard two-step Bertrand process. First, buyers simultaneously submit bids. The highest bid determines the asset price, p. Second, given p, the bank chooses whether or not to sell the asset. In the event the bank agrees to a sale, the winning bidder earns the asset's mature value (e.g., the asset's basic value plus its random dividend) less the asset price, or $\theta + \varepsilon - p$. For all other bidders as well as for the winning bidder in the case the bank rejects the bidder's offer, the payoff is zero.

Given the asset's expected value, risk neutral buyers should bid $p = E(\theta)$, and the winning bid is selected at random from among the tied bids. The dashed line in Fig. 1 shows the price that buyers are willing to pay as a function of the asset's expected value. Conformance of auction outcomes with assets' expected values is our first hypothesis

Hypothesis 1. *Winning asset bids equal the asset's expected value.*

[5] For general reviews of policy experiments see Normann and Ricciuti (2009) and Roth (2016).

[6] In a number of instances experimentalists have compared the decisions of college undergraduates with actors in pertinent natural contexts, and in the vast bulk of instances experimentalists found no significant differences in behavior. See Frechette (2016) for a review of these experiments.

[7] Kiss et al. (2021) provide a recent review of the experimental literature on financial fragility. For a review of policy experiments conducted to evaluate responses to the 2007-2009 financial crises see Davis and Korenok (2022).

[8] An extensive stream of experimental research initiated by Nagel (1995) shows that in a beauty contest framework, laboratory participants not experienced with a particular environment very typically deviate markedly from the best response to fully rational rivals. Deviations can be classified in terms rationality levels: For example 'level 1' play is defined as a best response to random, 'level 0' choices, and 'level 2' play is a best response to level 1 decisions. Subsequent levels are defined iteratively, with level n defined as a best response to level n-1. The preponderance of laboratory participants make choices consistent with play below level 2, far from the fully rational response (Camerer et al., 2004).

[9] Note that Goldstein and Leitner do not analyze an interbank market, but rather a simpler structure in which a bank engages in risk sharing activity by offering shares of the bank's assets to bidders. The authors observe, however, that the nature of their results remains the same if banks enter into risk sharing arrangements among themselves rather than with a market, provided that the idiosyncratic risk is fully diversified within the group. See Goldstein and Leitner (2018) p. 55, Section 7, comment 2. Perhaps more critically, as mentioned in the text, interbank markets are hardly banks' only liquidity source. Short term funds secured through money markets routinely make up a substantial portion of bank liabilities. Variations in disclosure conditions affect the willingness of financial markets to provide banks with liquidity in a way that very closely parallels the analysis outlined in the text.

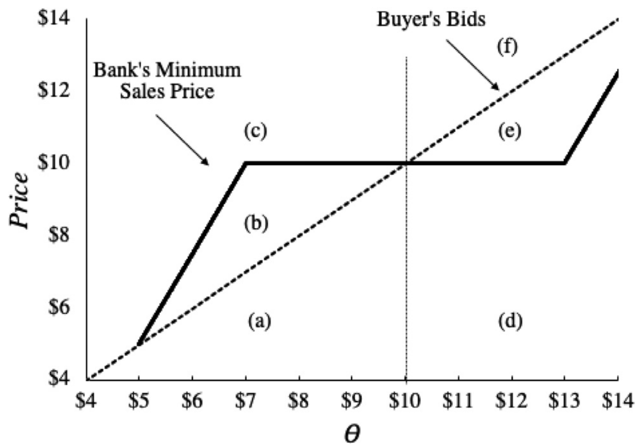

Fig. 1. Predicted buyers' winning bids and banks' minimum sales prices. *Key:* The dashed line illustrates the asset's expected value. The solid line shows the bank's minimum sales price given a basic value θ, which is non-linear because of the r=$15 bonus that the bank receives in the event that either the sales price or the final asset value exceeds $10. Letters (a)–(c) indicate ranges where winning bids are below the expected winning bid, between the asset's expected value and the banks minimum sales price, and above the bank's minimum sales price when basic value θ is less than $10. Letters (d)–(f) identify comparable winning bid ranges when the basic value θ exceeds $10.

Technically, this simple market structure is an auction. Buyers simultaneously submit offers for an asset whose conditional expected value is common knowledge, and the highest bidder wins the asset if the bank accepts the offer. This environment, however, differs from any standard structure analyzed in auction theory because here all bidders possess the same information and valuation for the item sold. The standard auction structure closest to our environment is the first-price common-value auction, but our environment differs critically from the first-price common-value auction in that buyers receive no private signal or any other private information that would allow the construction of a meaningful equilibrium bid function.

Overbidding is a pervasive feature of first-price common-value auctions (see e.g., Kagel and Levin 1986), and despite the differences between that auction structure and our environment, we may still observe overbidding.[10] To mitigate the risk that the overbidding will interfere with other predictions, we conduct a treatment in which we automate buyers in addition to a treatment with real buyers. Automated buyers behave exactly as hypothesis 1 predicts by bidding the asset's expected value.

2.1.2. Banks

Given a price, the bank may either sell the asset or hold it to maturity. Let z denote the bank's final cash holding. If the bank sells the asset then its final cash holding equals the sales price $z = p$. If the bank holds the asset until maturity, the final cash holding equals the asset payoff $z = \theta + \varepsilon$. In either case the bank realizes a bonus r=$15 if its final cash holding weakly exceeds $10. That is, the bank's payoff, $R(z)$ is discontinuous:

$$R(z) = \begin{cases} z \; if \; z < 10 \\ z + r \; if \; z \geq 10. \end{cases}$$

Using the terminology developed in Fostel and Geanakoplos (2015), one can think of the specific situation modelled by Goldstein and Leitner as a bank that invests deposits into two types of assets: *financial assets*, which are liquid assets that can be sold to buyers in a competitive market subject to random shocks, and *nonfinancial assets*, which are bank specific investments that are illiquid and can be sold by the bank prior to maturity only at a deep discount. The bank's portfolio generates a bonus of $15 if the nonfinancial assets are held to maturity. The model analyzes the bank's response to 'stress' in the form of an unexpected need for $10 in deposits, as might happen if the bank becomes aware that a creditor will refuse to roll over a short-term loan that matures in the near future. If the bank can immediately sell its financial assets for $10 or more, it will do so, allowing the bank to cover the upcoming cash shortfall without having to liquidate its nonfinancial assets, and thus allowing the bank to realize the bonus. If, however, the current market price for the bank's financial assets is less than $10, the bank may still hold its financial assets in the short term, in the hope that the price will rise. If the value of the bank's financial assets remains below $10, the bank must liquidate its nonfinancial assets to cover the shortfall to pay depositors, and forgo the bonus. [11]

The discontinuity in $R(z)$ creates a non-linearity in the bank's minimum acceptable sales price, as shown by the solid black line in Fig. 1. To see this, suppose that in any period, the bank knows the realization of its asset's basic value, but only the distribution of its random dividend. The bank's expected return from holding an asset is the sum of the asset's basic value, plus the probability-weighted value of the bonus. A risk neutral bank will sell the asset whenever the return from selling exceeds the bank's expected payoff for holding asset to maturity, or $E(R)$, which is given by the formula

$$E(R) = \theta + \left(\frac{\theta - 5}{10}\right) \times \$15. \tag{1}$$

Consider $\theta = \$6$, for example. In this case the bank's expected payoff for holding the asset is $E(R) = \$6 + .1(\$15) = \$7.50$, implying that the bank must receive at least $1.50 over the asset's expected value to agree to a sale. The pattern of demanding prices in excess of the asset's expected value continues as long as $\theta < \$10$. As indicated in Fig. 1, however, when the asset's expected value exceeds $7.00, the bank stops demanding the asset's full expected return from holding the asset, because selling for $10 increases to one the probability of realizing the bonus, which in turn raises the bank's return from selling the asset above the bank's expected return from holding it. With $\theta = \$9$, for example, the bank's expected payoff for holding the asset to maturity is $E(R) = \$9 + .4(\$15) = \$15$. If the bank sells at a price of $10 uncertainty is eliminated, and $R = \$10 + \$15 = \$25$. Thus, the bank should sell for $10 even though $p < E(R)$. Using the same logic, the bank will continue to agree to sell its asset for $10, even when the asset's basic value rises above $10. With $\theta = \$11$, for example, the bank's expected payoff for holding the asset to maturity is $E(R) = \$11 + .6(\$15) = \$20$, still below the $25 return for selling the asset for $10. More generally, the risk neutral bank will sell for $10 any asset with any basic value between $7 and $13, and would demand more than

[10] Overbidding occurs in first-price common-value auctions even among "super-experienced" bidders who have learned to overcome the winner's curse in common-value auctions. Kagel and Richard (2001) explore reasons why these "super-experienced" bidders continue to overbid. They consider a joy of winning factor, rivalrous bidding motives, limited liability, and risk preferences, all of which could be factors in our experiment. The strongest explanation for persistent overbidding that Kagel and Richard find, however, is that bidders settle on non-optimal, but still profitable rules of thumb. This same reasoning would not apply in our environment because overbidding is never profitable in expectation.

[11] Unlike the simpler situation modelled by Diamond and Dybvig (1983), where the unanticipated early deposit withdrawals induce the immediate need to liquidate nonfinancial asset, the need for a bank to recover liquidity may be anticipated rather than imminent. This anticipated need may leave the bank with some discretion as to when and under what condition to sell assets, the situation Goldstein and Leitner analyze. A large portion of a modern bank's liabilities typically consists of repurchase agreements and other subordinated debt in addition to demand deposits. Concerns that lenders may fail to roll over these agreements can create anticipated liquidity shortages, in which case the bank may consider selling assets.

Table 1
Prices, sales and bonus incidence predictions.

	No Disclosure	Partial Disclosure	Full Disclosure
Prices	$p =$ \$6	$p(M/H) = \$11^*$ $p(L) = \$6$	$p(H) = \$13^*$ $p(M) = \$9$ $p(L) = \$6$
Expected Bonus Incidences	43%	70%	50%

Key: $p(\#)$ indicates the equilibrium price in disclosure condition #. An * aside a price indicates that a sale occurs in equilibrium.

\$10 only for $\theta > \$13$.[12] Thus, the theory predicts that for a range of basic values below \$10, banks will decline offers greater than or equal to the asset's expected value (indicated as area (b) in Fig. 1), and for a range of basic values above \$10, the bank will agree to sell at prices below the asset's expected value (indicated as area (e) in Fig. 1). Our second hypothesis allows evaluation of banks' behavioral conformance with this sales prediction.

Hypothesis 2. Banks sell assets only if the bid price exceeds the minimum acceptable sales price.

2.1.3. Regulators

Efficiency-enhancing risk sharing occurs if the market pools assets, some of which would not be sold on their own, so that the average basic value of the pooled assets weakly exceeds \$10, and thus allows an increased number of banks to realize the bonus. The regulator's disclosure rule determines the possibility of such risk sharing. We consider three disclosure rules, or asset ratings schemes. In a first 'no disclosure' scheme buyers are offered a single rating for all three possible basic value realizations $\theta = \$6$, $\theta = \$9$, and $\theta = \$13$. This scheme conveys no basic value information to buyers. A second 'partial' disclosure scheme divides assets into two classes, a class L for a \$6 basic value realization and a class MH for the \$9 and \$13 basic value realizations. Finally, a 'full disclosure' scheme reports a separate rating for each of the three basic value realizations: a rating of L if the basic value is \$6, M if the basic value is \$9, and H if the basic value is \$13.

These three ratings schemes cleanly separate desirable and undesirable effects of disclosure rule variations. Under a 'no disclosure' scheme no trade will occur. For basic value realizations of \$9 and \$13 the pooled asset's expected value, $E(\theta) = \frac{6+9+13}{3} = \$9.33$ is less than the \$10 minimum sales price risk neutral banks would demand and no sales would occur. Banks would agree to sell an asset with a \$6 basic value for the pooled assets' expected value, but the fact that banks would agree to sell only assets with \$6 basic value realizations at a price of \$9.33 induces a lemons market effect, driving the winning bid down to \$6. Since the bank's expected payoff for an asset with a \$6 basic value is \$7.50, the bank will keep the asset until maturity instead of selling it.

At the other extreme, a full disclosure scheme provides too much information to the market. When both buyers and the bank know with certainty the asset's basic value, trade would occur only for the \$13 realization, since only in this case does the price that buyers are willing to bid exceed the bank's minimally acceptable price. Thus, a full disclosure scheme allows no risk pooling.

Risk pooling opportunities arise only with a partial ratings scheme. As observed previously, in the event of an L rating when $\theta = \$6$ no trade would occur, since $E(R) > p$. The expected value of the pooled M and H assets, however, $E(\theta) = \frac{\$9+\$13}{2} = \$11$ would induce banks to sell both \$9 and \$13 realizations, since a winning bid p=\$11 exceeds the bank's minimum acceptable price of \$10 for either basic value. The entries in the top row of Table 1 summarize price and sales predictions.[13]

To this point, we have assumed that banks know their basic value realization when bids are submitted. In some instances, however, banks might be uncertain about their asset's basic value. A bank's portfolio of financial assets, for example, might include large tranches of thinly traded collateralized debt obligations, which may be difficult to value prior to an attempted sale, but about which a regulator may have better information. Goldstein and Leitner analyze the case where banks as well as buyers are uninformed, and correspondingly, we evaluate it in our experiment as well.

In what follows we term those banks who are unaware of their asset's basic value as 'uninformed' banks, which we distinguish from 'informed' banks who know their asset's basic value. As a theoretical matter, banks' knowledge of basic value affects only the equilibrium price prediction in the no disclosure scheme. In that case, the price prediction rises from \$6 to \$9.33 because banks' ignorance of basic value eliminates their ability to sell only \$6 realizations at the average expected value of the three asset realizations. Despite the price increase, the no-trade prediction remains in effect because the uninformed banks will reject the offer, since the expected value of holding the asset until maturity, at $\$9.33 + \frac{4.33}{10}\$15 = \$15.83$ far exceeds the \$9.33 offer. Thus, no trade (and no risk pooling) would occur. We evaluate the behavioral effects of not telling banks their asset's basic value as a third hypothesis, which we articulate in terms of the theoretical prediction.

Hypothesis 3. *Banks' uncertainty about their asset's basic values affects market outcomes only under a no disclosure regime. In this case, the winning buyers' bids rise from \$6 to \$9.33 Nevertheless, no sales will occur.*

Our final hypothesis pertains to the efficiency-enhancing effects of the partial ratings scheme. Bonus incidences represent a measure of market efficiency because trades at prices above \$10 can increase likelihood of banks' receiving bonuses which otherwise would not be realized in the market, thereby creating a trade surplus. Disclosure variations affect expected bonus incidences, as show in the bottom row of Table 1. Under the no disclosure scheme no sales occur and banks will hold all assets

[12] As is clear from (1), when $\theta = \$13$ the expected return from holding the asset equals \$25. Note, however, that even in this case the bank would strictly prefer to sell the asset rather than hold it for prices above \$10, but below its expected value of \$13.

[13] The selection of {\$6, \$9 and \$13} as the set of basic value realizations is not arbitrary, but is almost completely dictated by the underlying assumptions in the Goldstein and Leitner development, along with some simplifying conditions imposed to facilitate understanding of the environment by participants. (Most prominently, we restrict basic value realizations to integers.) See Appendix A for details. While sparse, our streamlined environment effectively captures the behavioral issues underlying the Goldstein and Leitner development. In any variant of their model, the pooled value of all assets combined must fall below the bonus cutoff, while the expected value of the optimally pooled asset must exceed the bonus cutoff. Also, for pooling to improve risk sharing, at least one of the assets in the optimal pooling must fall below the bonus cutoff. The key behavioral issues in the model turn on bidding decisions and the way banks respond to winning bids in the neighborhood of the cutoff, as reflected in our laboratory implementation.

to maturity. In this case the expected bonus incidence is simply the percentage of instances for each draw of the basic value where the bank realizes a final asset value in excess of $10, or .1(1/3) + .4(1/3) + .8(1/3) = 43%. With the full disclosure scheme sales occur only when the basic value draw equals $13, increasing to certainty the likelihood of a bonus in that case, and thus raising the expected bonus incidence to .1(1/3) + .4(1/3) + 1 (1/3) = 50%. Finally with the partial disclosure scheme sales occur for both $9 and $13 basic value realizations, and thus generates an expected bonus incidence of .1(1/3) + 1 (1/3) + 1 (1/3) =70%. On net then, the partial rating scheme raises the expected bonus incidence rate by 27 percentage points relative to the no disclosure scheme and 20 percentage points relative to the full disclosure scheme. This is our fourth hypothesis.

Hypothesis 4. *The incidence of banks receiving bonuses is higher under a partial ratings scheme than under either no disclosure or full disclosure schemes.*

2.2. Experiment procedures

To evaluate hypotheses 1 to 4 we conducted an experiment which consisted of a series of eight laboratory sessions, six with real buyers and two with automated buyers. In each session, a cohort of participants was randomly seated at visually isolated computer terminals. A monitor then read the instructions aloud, assisted by a copy projected on a screen at the front of the lab, as participants followed along on their printed copies of their own.[14]

In the sessions with real buyers, the instructions explain that participants are anonymously divided into 4-player markets. Each market consists of one bank and three buyers who bid for a stochastically-valued bank asset in a series of trading periods. Both market groupings and player roles remain fixed throughout all periods.[15] To help both banks and buyers understand the range of possible mature asset values, the instructions include a table that illustrates possible final asset valuations for each basic value (which we henceforth refer to as BV) in e$1 (e.g., lab dollar) increments, along with the added explanation that each basic value realization is equally likely, and that on average the dividend value will be 0.

Each period proceeds in two-steps. First, buyers, endowed with the combination of an e$5 bequest, an e$10 working capital loan, and a rating of the available asset's basic value, simultaneously submit bids for the asset. To facilitate bid formation, buyers are shown the possible basic values that correspond to each rating given the disclosure condition in use. Second, once a winning bid is determined, the bank elects to either sell the asset to at a price equal to the high bid or keep it to maturity. Following the bank's decision, the final asset value is revealed, earnings are determined and the period ends. Buyers earn the e$5 endowment each period plus, in the event the buyer bought the asset, the difference between the final asset value and the purchase price. The bank earns the asset revenue (either the final asset value or the sales price) plus the e$15 bonus if the asset payoff or the sale price exceeds e$10 in the period. To achieve parity between buyer and banker earnings while maintaining a common conversion ratio between experimental dollars and U.S. dollars for both types, banks also pay a flat e$10 'tax' each period.

[14] Sample Instructions appear as Appendix C.

[15] The fixed matching of participants over multiple rounds creates a potential for repeated game effects in the form of buyer collusion. Absent market power, however, collusive outcomes in posted price markets with three or more players is rare, and presents even less of a concern when a seller (the bank) decides whether or not to accept winning bids. As will been seen in the results, collusion (which in these markets would occur as bids below an asset's expected value) was rare.

Table 2
Matrix of treatments.

	Disclosure Sequence (# of participants)		
	NFP	*FPN*	*PNF*
Real Informed	RI1 (20)	RI2 (20)	RI3 (24)
Real Unformed	RU1 (20)	RU2 (20)	RU3 (20)
Automated Informed	AI (5)	AI (5)	AI (5)
Automated Uninformed	AU (4)	AU (5)	AU (5)

Note: '*N*' denotes no disclosure, '*F*' full disclosure, '*P*' partial (optimal) disclosure.

Following the instructions, participants completed a short quiz of understanding. In the event a participant answers a question incorrectly, the pertinent segment of the instructions was explained again. After completing the instructions, participants made decisions in an initial practice period that was conducted to familiarize them with the environment. Participants were not paid for their decisions in the practice period, but were invited to privately ask any questions they might have had about procedures. Following the practice period, the paid periods commenced.

Sessions were divided into three 15-period sequences. In each sequence, the ratings scheme ('No', 'Partial', or 'Full') remained fixed. Following the 15^{th} and 30^{th} periods the session was paused and the ratings scheme for the subsequent sequence announced. Following the 45^{th} period the risk-pooling experiment ended, participants were subsequently paid privately and dismissed one at a time.[16] To control for potential order of sequence effects we rotated ratings schemes across sessions, as shown in Table 2.

Procedures for the automated buyer sessions duplicated those for the real buyer sessions with two differences. First, the initial offer stage of each period is replaced by an automated buyer who uniformly bids the asset's expected value in light of the disclosed information. Second, treatments were condensed into two sessions, one with value informed banks and the other with uninformed banks. To generate an experience profile comparable to that generated in the real buyer sessions, the participant cohort in each session was anonymously subdivided into three groups, with each group following one of the three rotation sequences used in the real buyer sessions.

Sessions were programmed with the z-Tree software (Fischbacher, 2007). Participants were 153 undergraduates enrolled at Virginia Commonwealth University in the spring semester of 2019 and were recruited with the ORSEE recruiting system (Greiner, 2015). Most were upper-level engineering, math, business, and economics students. Sessions lasted 45–60 min. Lab dollar earnings were converted to U.S. currency at a e$15=$1 U.S. rate. Earnings ranged from $11.70 to $47.30 and averaged $23.40.

3. Results

The winning bid distributions shown as the upper and lower panels of Fig. 2 provide an overview of experimental outcomes in the real buyer sessions.[17] As a rough control for learning and ad-

[16] Prior to ending the session participants also completed a salient risk elicitation exercise. Our measure of participants' risk preferences was not a statistically significant factor in variants of our regressions of bidding behavior (p=0.449 in bid regressions for the informed banks treatment and p=0.649 in bid regressions for the uninformed banks treatment.) The main results of this paper are robust to the omission of our measure of risk preferences.

[17] Here we focus on winning bids. Means and standard deviations for all bids (including losing bids) are reported in Tables B0.1 and B0.2 in Appendix B. For succinctness, the panels in Fig. 2 also pool winning bids for $\theta = \$6$ realizations in the full and partial disclosure ratings scheme. Each of these conditions present the same basic value information to both bidders and banks.

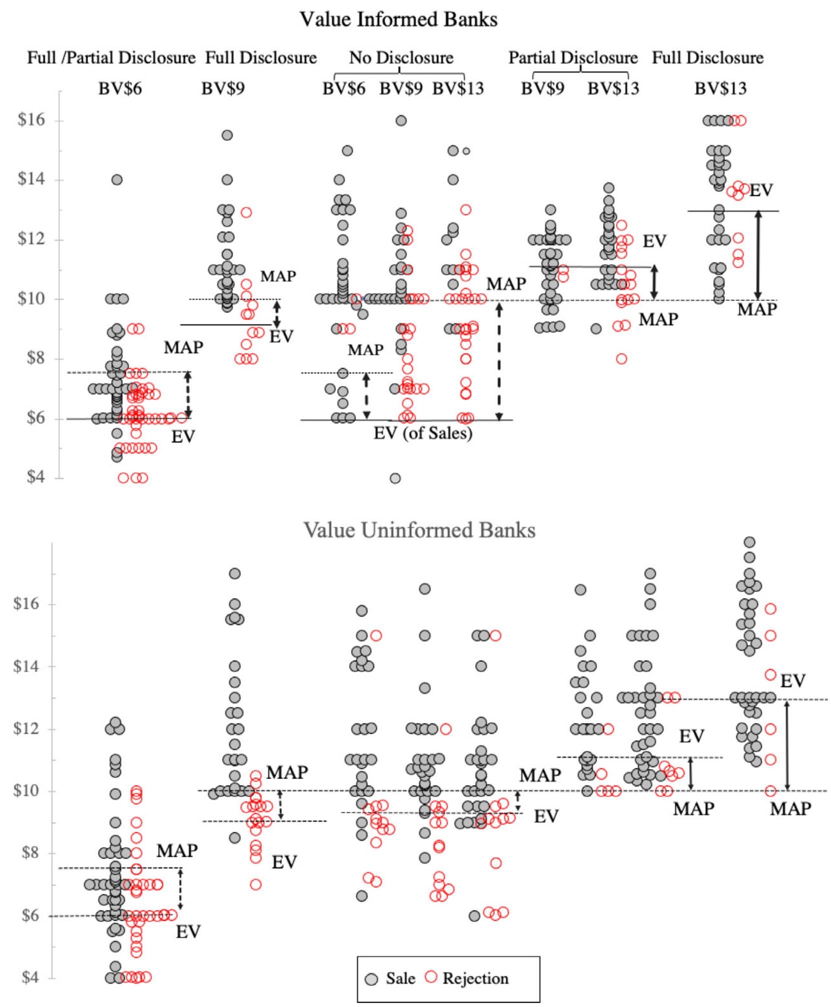

Fig. 2. Winning Bid Acceptances and Rejections, Last 8 Sequence Periods of the Treatments in the Real Buyer Sessions. *Notes*: Solid and hollow circles represent accepted and rejected bids, respectively. EV denotes the asset's expected value (to buyers), while MAP denotes the bank's minimum acceptable price. BV$X, X∈ {$6, $9, $13}, denotes the asset's basic value in the column.

justment, the figures illustrate winning bids only for the final eight periods of each 15 period sequence.[18]

Taken together, the two panels of Fig. 2 illustrate several primary results of the real buyer sessions. First, expected value realizations for bidders (denoted as EV's) largely fail to organize winning bids. In both the informed bank and uninformed bank sessions, winning bids are both highly dispersed and frequently in excess of the asset's expected value. Second, although banks generally reject low winning bids (the hollow red circles) and accept high ones (the solid grey circles), failures to both reject and to sell when predicted occur in a non-trivial number of instances. Third, looking at the informed bank regime shown in the upper panel of the Figure, observe that the e$6 prediction largely fails to organize winning bids in the 'No Disclosure' scheme. Instead, the distribution of winning bids in the No Disclosure scheme are quite similar in both the Informed Bank and Uninformed Bank regimes. More generally bid distributions across the Informed and Uninformed Bank sessions are quite similar. The one notable difference is the pooled Medium / High value realizations in the Partial Disclosure scheme, where winning bids tend to be somewhat more restrained in the Informed Bank regime. As suggested by the hollow dots above the minimum acceptable price ('MAP') in the e$13 realization of the Medium/ High value pooling, informed banks were reluctant to accept bids below the asset's expected value, which had the effect of driving down bids, as buyers realized an increased incidence of sales with e$9 realizations. Finally and fourth, the propensity for bids to exceed banks' minimum acceptable price suggests that bonus incidences in all disclosure regimes will exceed predicted levels. To confirm the above impressions, we more formally evaluate hypotheses 1 to 4 in the sections that follow, starting with an analysis of winning bids**.**

3.1. Winning bids

To evaluate the proximity of winning bids in the real buyer sessions to expected asset values we regress the deviation of winning bids from asset expected values against a series of indicator variables that denote the disclosure scheme, the asset's expected payoff and the bank information condition. Specifically, we estimate

$$y_{gt} = D\beta + e_{gt} \tag{2}$$

where y_{gt} denotes the deviation of the winning bid from the asset's expected value for bidders of group g in period t and $\mathbf{D}$ denotes a matrix of indicator variables that allows unique identification of each expected value realization $\{\$6, \$9, \$9.33, \$11, \$13\}$ in each disclosure scheme {*n*one, *p*artial, *f*ull}, and in each information condition {*i*nformed, *u*ninformed} for the real buyer sessions.

[18] We illustrate only the last 8 periods of each sequence as a rough control for learning and initial adjustment effects.

Table 3
Mean deviations of winning bids from asset expected values. Last 8 periods of each sequence.

Bank Basic Value Information		Ratings Scheme /Expected Value				
	F$6	P$6	F$9	N$9.33	P$11	F$13
Informed	0.55 (0.30)	1.00** (0.28)	1.87** (0.44)	0.55 (0.47)	0.12 (0.24)	0.30 (0.58)
Uninformed	0.72 (0.55)	1.33** (0.34)	1.92** (0.49)	1.03*(0.45)	1.11** (0.35)	0.85 (0.54)
		Differences Across Bank Information Conditions				
	-0.17	-0.33	-0.05	-0.48	-0.99°	-0.55

Key: *, ** reject H_o that the winning bid does not deviate significantly from the asset's expected value $p<0.05$ and 0.01, respectively. °, °° reject H_o that the provision of basic value information to banks does not affect winning bid deviations at $p<0.05$, and 0.01, respectively.

To control for possible group effects we cluster by group, and use a White 'sandwich' estimate to control for unspecified heterogeneity or serial correlation.

Regression results for periods 8-15 of each sequence appear in Table 3. [19] The uniformly positive mean deviations and large standard deviations in Table 3 reflect the generally high and variable winning bids illustrated in Fig. 2. Further, despite the winning bid variability, mean deviations differed significantly from zero in seven of the twelve comparisons, including realizations in ratings schemes that allow bidders to know the basic value with certainty, such as the mean deviations of at least e$1.87 in the F$9 full disclosure/basic value condition for both informed and uninformed banks and mean deviations of at least e$1 in the P$6 partial disclosure/basic value condition for both informed and uninformed banks. Winning bid deviations also differed significantly from 0 for value-uninformed banks in the N$9.33 no disclosure and P$11 partial disclosure conditions, and in the F$6 full disclosure condition when banks are value informed. We summarize these observations into our first finding, which is largely a rejection of hypothesis 1.

Finding 1. *Winning bids are highly variable, and in many ratings scheme/disclosure conditions significantly exceed the asset's expected payoff.*

Both the variability and the extent of overbidding deviate markedly from predicted behavior. Significantly, the overbidding behavior was quite costly for buyers. The propensity for winning bids to exceed the assets' expected values resulted in *ex post* losses in more than 30% of periods in all conditions except the P$6 condition with informed banks, and even here the winning bidder suffered a loss in 20% of periods.[20]

As mentioned previously, the posted bid structure used to in our environment resembles a common-value auction, with the critical difference that bidders share common uncertainty about the value of the asset. Prior to evaluating the other hypotheses, we consider briefly the factors driving the observed deviations. An analysis of buyers' bid adjustment patterns reported in Appendix B suggests that much of the persistent bid variability is driven by myopic responses to the idiosyncratic component of assets' final values. Rather than averaging out the effects of idiosyncratic dividend realizations, buyers persistently base bids on the final value of the most recent previous instance of a ratings scheme/expected value realization, reducing bids in response to a low idiosyncratic dividend outcome and raising them in response to a high dividend outcome. The observed propensity for overbidding may be driven by *ex post* regret for failing to win auctions that turn out to have high dividends. Buyers who overbid in the last pertinent instance of a ratings scheme/expected value realization, for example, tend to raise their already high bids still further in the subsequent realization if they failed to win that auction. This sort of bidding pattern is consistent with a stylized sort of rivalrous behavior in which bidders enjoy a utility of winning when the value of the asset is high. We summarize these observations with the following comment.

Comment 1. *In our environment buyer bidding patterns appear to be driven by the final value of the most recent previous instance of a ratings scheme/expected value realization. This behavior is consistent with a sort of rivalrous behavior in which bidders enjoy a utility of winning when they (incorrectly) expect the value of the asset to be high.*

The generality of this sort of rivalrous motivation for bidding merits further investigation. We suspect that it would likely not extend to richer environments where the funds used in bidding were based on deposits and other bank liabilities (as in an interbank market) or where diffuse buyers could use available funds to bid for multiple assets (as in money markets).

Returning to the bid deviation estimates in Table 3, observe that the estimation results shown in the bottom row of the table also allow evaluation of the effects of altering banks' basic value information on winning bids. Although mean winning bid deviations are smaller for informed banks in five of the six ratings scheme/expected value conditions, the deviation is significant only once, in the P$11 condition, where the mean bid deviation rises by e$0.99 with uninformed banks ($p<.01$). Notably, mean winning bid deviations fail to differ significantly across bank information conditions in the no disclosure (N$9.33) ratings scheme. In this case taking away the basic value information from banks resulted in an e$0.48 increase in the mean bid deviation, far smaller than the predicted e$3.33 difference (from e$6 to e$9.33). [21] This is our second finding, which is a rejection of hypothesis 3.

Finding 2. *Banks' knowledge of basic asset values significantly affects winning bids only in the high value realization of the partial disclosure ratings scheme (where no difference is predicted). Banks' information about basic value does not significantly affect bids in the no disclosure ratings scheme (where a difference is predicted).*

The unpredicted effect of bank information on bidding behavior in the partial disclosure scheme would be consistent with a bias in

[19] As was the case for Fig. 2(a) and (b) we restrict observations to the last eight periods of each 15 period sequence to control for learning and initial adjustment effects. Importantly, focusing on decisions in the final 8 periods does not importantly affect results relative to estimates the use other sub-sequences periods as the basis of analysis. Tables B3.1 and B3.2 in Appendix B repeat the estimates reported in Tables 3 using all periods, the last 10 periods and the last 5 periods of each sequence as the basis for analysis. As can be seen from comparison of these alternative estimates with those based on the last 8 sequence periods, although adjustments did occur in some instances, these adjustments are largely confined to initial periods, and there is no consistent evidence of further adjustment after period 8. Moreover, Findings 1 and 2 are robust to each choice of sequence periods as the basis of analysis.

[20] Winning Bidder Loss Rates appear as Table B1 in Appendix B.

[21] The estimates are deviations from the assets' (pooled) expected values. In all cases but one, the predicted deviation from the expected value is zero in equilibrium. The exception is the no disclosure scheme with informed banks. In this case the equilibrium price is e$6, e$3.33 below the pooled expected value of e$9.33.

bank sales decisions toward making sales in terms of an asset's expected value rather than the asset's predicted minimum acceptable price. If banks with e$13 value realizations frequently declined to make sales for winning bids at or above the asset's e$10 minimum acceptable price (as suggested in Fig. 2 by the many hollow circles at or above e$13 for value informed banks in the partial disclosure scheme), buyers would find themselves making sales predominantly for e$9 realizations, causing bids to fall as winning bidders frequently realize losses *ex post*. As will be seen in the analysis of sales decisions in the next section, banks did frequently exhibit this 'expected value' bias in making sales decisions.

3.2. Bank sales decisions

To more formally evaluate bank sales decisions, we pool winning bids into two groups, one that includes all bank expected basic value realizations below e$10 and the other that includes all bank expected basic value realizations above e$10. Within each pooling we divide winning bids by their location relative to the underlying asset's expected value and the bank's minimum acceptable price, as shown by the letters *a* to *f* in Fig. 1. [22] For the pooling that includes assets with an expected value below e$10, we denote as area *a* the instances where the winning bid falls below the asset's expected value, area *b* the instances where the winning bid lies in the range above the asset's expected value but below the bank's minimum acceptable price, and area *c* the instances where the winning bid meets or exceeds the bank's minimum acceptable price. Areas *d, e* and *f* denote a comparable set of area for assets with an expected basic value above e$10: *d* indicates instances where the winning bid falls below the asset's minimum acceptable price, *e* indicates instances where the winning bid falls in the range that extends from the minimum acceptable bid up to the asset's expected value, and *f* indicates instances where the winning bid exceeds the asset's expected value. Bank behavior is consistent with equilibrium predictions if banks choose to sell in areas *c, e* and *f*, but decline to sell for bids in areas *a, b* and *d*. Of primary interest are decisions in areas *b* and *e*, because theoretical predictions regarding the circumstances under which efficient risk pooling occurs turn on decisions in this range.

Given this partition of the expected value/bid space, we estimate the following linear probability model:

$$y_{gt} = \mathbf{D}\beta + e_{gt} \tag{3}$$

Where y_{gt} takes on a value of 1 in the event the bank in group g chooses to sell in period t, and 0 otherwise. $\mathbf{D}$ is a matrix of indicator variable combinations that allow for unique estimation of sales probabilities for the winning bid/ expected value realizations $\{a, b, c, d, e, f\}$, in each bank value information condition $\{u, i\}$. As with winning bid estimates, we restrict attention to periods 8-15 to control for learning and adjustment effects and use a White 'Sandwich' estimator to control for unspecified serial correlation and heteroskedasticity.[23] Finally, we estimate the real and automated buyer sessions separately.

Summary regression results, shown as Table 4, suggest some general conformance with predictions. With real buyers, sales frequencies in areas *c* and *f* were at least 79%, indicating that sales typically occur when the winning bid exceeds both the asset's expected value and its minimum acceptable price. Similarly, when the winning bid falls below both the asset's expected value and its minimum acceptable price, sales occur infrequently (areas *a* and *d*), and for informed banks, sales probabilities do not differ significantly from 0.[24] All of these outcomes are consistent with predicted equilibrium behavior.

Nevertheless, equilibrium predictions organize observed sales frequencies incompletely. Particularly large deviations occur in areas *b* and *e*, where sales decisions drive the predicted effects of partial disclosure. With real buyers, in area *b* sales incidences of 58% for informed banks and 47% for uninformed banks both significantly exceed the predicted level of 0% by substantial margins ($p<.01$ in both cases). Again, in area *e* sales incidences of 65% of informed banks and 76% for uniformed banks fall significantly below the predicted 100% level in area *e* ($p<.01$ for informed banks and $p<.05$ for uninformed banks).

As seen from estimates for the automated buyer sessions, shown in the bottom rows of the table, the deviation of sales decisions from predicted behavior persists is not driven by buyer overbidding. Even with automated buyers, banks deviate significantly from optimal behavior, agreeing to sales in area *b* between 32% and 35% of instances, when all bids should be rejected, and accepting offers in area *e* between 53% and 54% of instances, when all offers should be accepted. We summarize these observations as a third finding.

Finding 3. Banks sell assets with significantly higher frequencies when the winning bid exceeds the minimum acceptable price than not. Nevertheless sales decisions deviate substantally from predictions. In particular banks frequently sell assets at prices below the minimum acceptable price when expected values fall below the bonus cutoff, and frequently reject offers to sell assets at prices above the minimum acceptable price when expected values exceed the bonus cutoff.

3.3. Bonus incidences

The above results regarding the tendency for buyers to overbid, and for banks to frequently deviate from predicted sales decisions combine to suggest that disclosure scheme variations will impact bonus incidence frequencies by smaller magnitudes than the theory predicts. To directly evaluate the effects of disclosure scheme variations on bonus incidences, we regress bonus realizations against a matrix of indicator variables parallel to that in Eq. (3), with the differences that the dependent variable y_{gt} takes on a value of 1 in the event the bank in group g realized a bonus in period t, and 0 otherwise, and $\mathbf{D}$ is a matrix of indicator variable combinations that allow for unique estimation of bonus realizations sales by ratings scheme $\{n, p, f\}$, and bank information condition $\{u, i\}$. As with the previous estimations, we estimate bonus incidences in sequence periods 8-15 as a control for learning and adjustment, and use a White 'sandwich' estimator to control for

[22] Note that this bid classification scheme results in different terms for ranking winning bids across bank value information conditions for the N$9.33 and P$11 disclosure scheme/value realizations. Consider, for example, the range of bids between an asset's expected value and its minimum acceptable price (areas *b* and *e*). In the N$9.33 ratings scheme, winning bids between e$9.33 and e$9.99 define area *b* for uninformed banks regardless of the asset's basic value. For informed banks, however, winning bids between e$6 and e$7.49 define the *b* range for an e$6 basic value realization, winning bids between e$9.00 and e$9.99 define the *b* range for an e$9 basic value realization and winning bids between e$10 and e$13 define the *e* range for an e$13 realization. Similarly, given a P$11 realization, bids between e$10 and e$11 (inclusive) define the *e* range for uninformed banks. For informed banks, bids between e$9 and e$9.99 define the *b* range for an e$9 basic value realization and bids between e$10 and e$13 define the *e* range for an e$13 basic value realization.

[23] Tables B4.1–B4.4 in Appendix B repeat the estimates reported in Tables 4 using all periods, the last 10 periods and the last 5 periods of each sequence as the basis for analysis. Finding 3 below is robust to each choice of sequence periods as the basis of analysis.

[24] There were no instances of winning bids falling below the minimum acceptable price (of e$10) in area *d* when banks did not have basic value information.

Table 4
Sales Probabilities means (std. deviations) sequence periods 8–15.

Treatment	Expected Basic Value/Relevant Price Range					
	a	*b*	*c*	*d*	*e*	*f*
Real Informed	0.18^{bb} (0.12)	0.56^{**} (0.06)	$0.86^{\dagger\dagger bb}$ (0.04)	0.12^{ee} (0.08)	$0.64^{\dagger\dagger}$ (0.10)	0.79 (0.10)
Real Uninformed	0.33^{**} (0.06)	0.47^{**ee} (0.08)	$0.90^{\dagger\dagger bb}$ (0.03)	–	$0.73^{\dagger}$ (0.10)	0.91 (0.05)
Automated Informed	–	0.32^{**e} (0.06)	–	–	$0.52^{\dagger\dagger}$ (0.09)	–
Automated Uninformed	–	0.35^{**} (0.05)	–	–	$0.54^{\dagger\dagger}$ (0.10)	–
		Predicted Sales Probabilities				
	0.00	0.00	1.00	0.00	1.00	1.00

Key: $^{*,\,**}$ reject H_o that the probability of a sale does not deviate significantly from zero $p<0.05$ and 0.01, respectively (for *a, b* and *d* only). †,†† reject H_o that the probability of a sale does not differ from 1 at $p<0.05$ and 0.01 (for *c, e* and *f* only). $^{b,\,bb}$ reject H_o that the probability of a sale does not differ from that observed for basic value/winning bids that fall in area *b* (for areas *a* and *c* only). $^{e,\,ee}$ reject H_o that the probability of a sale does not differ from that observed for basic value/winning bids that fall in area *e* (for areas *b, d* and *f* only).

Table 5
Bonus incidences, means (std. deviations) sequence periods 8–15.

Treatment	Disclosure Regime		
	None	Partial	Full
Real Informed	$0.69^{**\dagger\dagger}$ (0.07)	$0.57^{**\dagger\dagger}$ (0.04)	$0.63^{**\dagger}$ (0.06)
Real Uninformed	$0.69^{**\dagger\dagger}$ (0.08)	0.64^{**} (0.04)	$0.62^{**\dagger}$ (0.06)
Automated Informed	0.36^{aa} (0.04)	$0.58^{**\dagger\dagger}$ (0.04)	0.44^{bb} (0.03)
Automated Uninformed	$0.33^{*\dagger aa}$ (0.04)	0.62^{**} (0.05)	$0.34^{\dagger\dagger bb}$ (0.05)
	Predictions		
Optimal	0.43	0.70	0.50
No Trade	0.43	0.43	0.43

Key: $^{*,\,**}$ reject H_o that the mean bonus incidence does not deviate from the no trade prediction at $p<0.05$ and 0.01, respectively. †,†† reject H_o that the mean bonus incidence does not deviate from the optimal prediction at $p<0.05$ and 0.01, respectively. ^{aa} reject H_o that the mean price does not differ across no disclosure and partial disclosure conditions $p<.01$; ^{bb} reject H_o that the mean price does not differ across partial and full disclosure conditions, $p<.01$.

unspecified heterogeneity or serial correlation. [25] Also as with the previous estimates, we conduct separate regressions for the real and simulated buyer sessions.

The regression results shown in Table 5 report mean bonus incidences by disclosure regime and buyer-type treatment. Looking first at the real buyer sessions summarized in the upper portion of the table, notice that in all disclosure schemes mean bonus incidences uniformly exceed the no trade prediction of 43%. As indicated by the asterisks, these differences are all significant at $p<.05$. The substantial overbidding observed in Section 3.1 drives these bonus incidences, as banks frequently sold assets for more than e$10 (thus securing the bonus) when the asset expected value was less than e$10. The impact of overbidding was particularly pronounced in the No Disclosure and Full Disclosure ratings schemes, where as indicated by the superscripted crosses, observed bonus incidences also significantly exceeded predicted bonus realization rates ($p<.05$). By way of contrast, bonus incidences fell below predicted rates in the partial disclosure scheme, significantly so in the informed bank regime, where banks realized bonuses in only 57% of periods, a full 13 percentage points below the predicted 70% rate. The combination of higher than predicted bonus incidences under no disclosure and full disclosure ratings schemes and lower than predicted bonus incidences in the partial disclosure scheme completely undermines any positive effects of risk pooling.

Turning to the automated buyer sessions, shown in the bottom rows of Table 5, notice that restricting winning bids to the asset's expected value dramatically reduces bonus incidences under both the no disclosure and full disclosure ratings schemes. Under the no disclosure ratings scheme bonus incidences not only fall toward the no trade prediction of 43%, but fall below it, to 36% for informed banks and 33% for informed banks. As indicated by the crosses, this latter deviation is significant at $p<.05$. Under the full disclosure scheme bonus incidences do not fall significantly below the no trade prediction, but nevertheless are below the predicted level of 50% for both informed and uninformed banks, at 44% and 34% respectively. Both of these differences are significant at $p<.05$. At the same time, the switch from real to automated bidders leaves bonus incidences in the partial disclosure regime essentially unaffected, rising for informed banks from 57% with real buyers to 58% with automated buyers, and falling for uninformed banks from 64% with real buyers to 62% with automated buyers.

The net effect, then, is that with automated buyers partial disclosure increases risk pooling as the theory predicts. Bonus incidences in the partial disclosure scheme exceed rates in the no disclosure scheme regime by 22 percentage points for value informed banks (58% vs. 36%) and by 29 percentage points for uninformed banks (62% vs. 33%). Again, bonus incidences in the partial disclosure scheme exceed rates in the full disclosure counterpart by 14 percentage points for informed banks (58% vs. 44%) and by 28 percentage points for uninformed banks (62% vs 34%). All of these differences are statistically significant at $p<.01$. These observations form our fourth finding.

Finding 4. *In treatments with real buyers, bonus incidences do not differ significantly across disclosure regimes. In treatments with automated buyers, however, when bids are constrained to equal the asset's expected value, partial (optimal) disclosure significantly increases bonus incidences and social welfare.*

3.4. Discussion

In treatments with real buyers overbidding undermines any amelioratory effects of a partial disclosure scheme. Overbidding may be driven by a variety of factors, including the absence of an alternative investment opportunity for bidders, as well as the posted offer institutional structure specified in the theory. Some combination of a richer action space for buyers and an alternative trading institution would likely generate bidding close to the

[25] Tables B5.1–B5.4 in Appendix B repeat the estimates reported in Table 5 using all periods, the last 10 periods and the last 5 periods of each sequence as the basis for analysis. As can be seen from the alternative estimates, finding 4 is robust to each choice of sequence periods as the basis of analysis.

asset's expected value. We leave for future investigation the task of exploring this issue. However, our automated buyer sessions, where buyers are constrained to bid exactly the asset's expected value, stand as a reference for the limiting case where buyers act in a perfectly competitive manner. Under this limiting condition, the partial disclosure regime increases bonus incidences as theory predicts.

Two additional aspects of Finding 4 merit further discussion. The first regards the effects of eliminating overbidding on bonus incidences. As a comparison of bonus incidences across real and automated buyers in Tables 5 makes clear, bonus incidences fall far more under no disclosure and full disclosure than under partial disclosure. The different placements of an asset's expected value realization in the three disclosure conditions drives the outcome differences. In the no disclosure condition, the pooled asset's expected value of e$9.33 lies just below the e$10 bonus cutoff. Even modest overbidding raises bonus incidences, as the sales of assets for e$10 or more will trigger a bonus. Again, in the full disclosure treatment, only slightly more aggressive overbidding will increase bonus incidences for assets with an e$9 basic value. In the partial disclosure regime, however, overbidding impacts bonus incidences much less markedly. Only spectacular overbidding would trigger bonuses for the e$6 realization, while asset sales for the *MH* pooling will trigger a bonus whether or not overbidding occurs. We summarize these observations as the following comment.

Comment 2. *Asset overbidding impacts bonus incidences far more extensively in the no disclosure and full disclosure schemes than in the partial disclosure scheme.*

A second aspect of disclosure rule variations that experimental results highlight regards the differential effects of bank decision errors on bonus incidences in each disclosure scheme when buyers do not overbid. To see this, consider expected bonus incidences under the three disclosure schemes when banks deviate completely from optimal behavior - that is, they sell when optimal behavior would have them decline a sale, and decline sales when optimal behavior would have them sell. Under the no disclosure scheme, such a 'complete deviation' strategy would have banks agreeing to make sales at e$9.33 (or e$6.00), which reduces the expected bonus incidence from 43% to 0%. In the full disclosure scheme a 'complete deviation' strategy would have banks agreeing to sales with e$6 and e$9 realizations, but then foregoing sales with an e$13 realization. The nonoptimal sales at e$6 and e$9 reduce expected bonus incidences from 10% and 40%, respectively, to 0, while the nonoptimal offer rejection at e$13 reduces the expected bonus incidence from 100% to 80%. Taking the average, in the full disclosure scheme a 'complete deviation' strategy reduces the expected bonus incidence from 50% to 27%. Finally, under the partial disclosure scheme a 'complete deviation' strategy would have banks agreeing to sales at a price of e$6 given a e$6 value realizations, but then foregoing sales at a price of e$11 for e$9 and e$13 realizations. In this case, the nonoptimal sale at a price of e$6 reduces the expected bonus from 10% to zero, while the nonoptimal rejection of e$11 offers for the e$9 and e$13 value realizations reduces the expected bonus rates from 100% to 40% and 80%, respectively. Taking the weighted average, under partial disclosure the 'complete deviation' strategy reduces the bonus incidence from 70% to 40%, still much higher value than 0% under no disclosure or 27% under full disclosure.

Essentially, optimal disclosure not only promotes risk pooling directly when banks make optimal decisions, but indirectly when banks behave non-optimally, because of the differing consequences of deviations. Most of the impact is driven by the asymmetric effects of deviating by selling assets with basic values just below the bonus cutoff for less than $10, as would occur under full or no disclosure conditions), and deviating by declining to sell the same asset for e$11 (as would occur under partial disclosure). The former deviation reduces the expected bonus incidence to 0, while the latter still leaves a 40% chance of realizing a bonus.

Changes in sales error rates impact expected bonus incidences in a continuous way, ranging from the expected bonus incidences of 43%, 70% and 50% for no, partial and full disclosure given optimal sales decisions, to expected bonus incidences of 0%, 40% and 27% for perfectly nonoptimal behavior.[26] Reasonable assumptions about error rates generate expected bonus incidences very close to that reported in Table 5. For example, with a 33% error rate (roughly comparable to the sales decisions in Table 4), expected bonus incidences are 29%, 60% and 42% for no, partial and full disclosure respectively, quite close to observed bonus incidences. We summarize these last observations as our final comment.

Comment 3. *Absent overbidding, partial disclosure yields higher expected bonus incidences than either no disclosure or full disclosure conditions even if banks deviate significantly from optimal sales decisions. For that reason, the ameliorative effects of risk pooling predicted in Goldstein and Leitner (2018) are extremely robust to behavioral biases in bank behavior.*

4. Conclusions

This paper reports an experimental implementation of a theoretical model by Goldstein and Leitner (2018) to behaviorally evaluate the capacity of disclosure conditions variations to affect risk pooling. Experimental results yield two important behavioral results. First, the effects of variations in disclosure schemes on risk sharing are sensitive to overbidding. Even relatively modest overbidding can undermine the benefits of optimal disclosure. As a policy matter, this result does not importantly impact the model's potential usefulness, because regulators are unlikely to be concerned about insufficient risk pooling when buyers are willing to pay more for bank assets. Rather, concerns about risk pooling arise during financial crises when buyers are reluctant to buy bank assets and the factors that lead to overbidding, such as a booming economy and general optimism, are absent.

The second primary result is that absent overbidding, optimal disclosure increases risk pooling largely as predicted even if banks deviate from optimal sales decisions. From a policy perspective, this finding is considerably more important. Admittedly, our streamlined laboratory implementation of the Goldstein and Leitner model is quite simple. Nevertheless, it is not difficult to imagine natural circumstances where loan officers or asset managers deviate from optimal decisions in the ways observed here. Loan officers and asset managers, for example, routinely evaluate financial assets in terms of the asset's expected value, without taking into account external considerations, such as the possibility that the bank will encounter stress if some total sales revenue objective is not satisfied. Decisions based on an asset's expected value would constitute errors of the type discussed here when the bank

[26] One qualification to this result regards the effects of an expected value bias on bonus incidences in the optimal disclosure scheme when traders are value informed. Given a price of e$11 value informed banks with an expected value bias would uniformly agree to sell e$9 basic value realizations but would decline to sell e$13 realizations. Buyers might respond by reducing their offer price to reflect the realized expected value of the pooled asset. Price reductions would not undermine bonus incidences, however, unless the offer price fell below e$10, which would happen only if banks exhibit an overwhelming expected value bias. To see this, let q denote the probability that a bank is an expected income maximizer (e.g., that the bank agrees to a sale of an e$13 asset). Then the expected value of the pooled asset will exceed the e$10 bonus cutoff as long as $\frac{1/2}{1/2+q/2}(\$9)+\frac{q/2}{1/2+q/2}(\$13) > \$10$. Solving $q > 1/6$ to This inequality is satisfied when q > 1/3. Thus, the price will not fall below e$10 unless the probability that a bank will sell an e$13 asset at the pooled price of the e$9 and the e$13 assets is less than 1/3.

as a whole is seeking to achieve some collective minimum return during financial stress. Of course, more theoretical work that includes the possibility of decentralizing non-optimal behaviors is necessary, but we regard our finding that the effects of disclosure variations on risk pooling are robust to a plausible sort of non-optimizing behavior as offering behavioral support for the Goldstein and Leitner model as a basis for policy implementation, to the extent that the assumptions underlying that analysis reflect the critical features of the banking environment.

Author contributions statement

Caleb Cox: Conceptualization, Formal Analysis, Methodology, Investigation, Writing- review & editing. Douglas Davis**:** Conceptualization, Investigation, Methodology Writing - original draft. Writing - review & editing, Funding acquisition. John Lightle**:** Conceptualization, Formal Analysis, Methodology, Investigation, Writing – original draft. Oleg Korenok**:** Conceptualization, Software, Investigation, Data Analysis, Writing - review & editing.

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Data availability

A link to original data, code and zTree files is available on Github.Data Availability: Github

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Appendix A. Explanation of basic value parameter choices

Our selection of basic value realizations of \$6, \$9, and \$13 are uniquely determined by a combination of the theoretical assumptions in the *Goldstein and Leitner* model, and some simplifying conditions intended to make the environment more easily understood. More specifically, for a model with three possible basic value realizations, the *Goldstein and Leitner* development requires that the basic value realizations satisfy the following conditions.

(a) For each possible realization the probability of a bonus r must be both strictly greater than zero and strictly less than one.
(b) Only the highest of the three realizations may exceed the bonus cutoff price p_b (so that full disclosure does not maximize risk-sharing).
(c) The sum of the highest value realization and the probability weighted value of bonus must not exceed the sum of the expected value of the two highest realizations pooled and the bonus (so that high value banks are willing to participate in risk-sharing).
(d) The expected value of the highest two realizations pooled must exceed the bonus cutoff (so that pooling increases risk-sharing)
(e) The expected value of all three assets collectively pooled must be less than the bonus cutoff (so that non-disclosure forecloses some risk sharing).

Label the three possible basic value realizations as x, y and z. Without loss of generality, assume, $x<y<z$. Given a bonus cutoff price $p_b = \$10$, an idiosyncratic risk range uniformly distributed over $\varepsilon \in [-5, 5]$, and r=\$15 these conditions reduce to the following

(a) $x>5$ and $z<15$
(b) $y<10$ and $z>10$.
(c) $z + (\frac{z-5}{10})15 < \frac{y+z}{2} + 15$
(d) $\frac{y+z}{2} > 10$, and
(e) $\frac{x+y+z}{3} < 10$.

Adding to these theoretical restrictions, we impose the following additional conditions for the purposes of simplicity in presentation

(a) Each of the basic value realizations must be integers
(b) The pooled value of y and z must be an integer.

These simplifying conditions restrict parameter choices as follows

(a)' $x \geq 6$ and $z \leq 14$
(b)' $y \leq 9$
(c)' $z < \frac{y}{4} + 11.25$
(d)' $\frac{y+z}{2} \geq 11$.

Combining (b)'and (c)' implies that the largest integer value for z is 13. Then (d)' implies that y =9. These values, along with condition (e) and the integer constraint implies that x=6 or x=7. Using x=6 creates the largest separation between the pooled expected value $\frac{x+y+z}{3}$ and 10.

Appendix B. Supplementary Tables

B.0. The evolution of bid variation across periods

Tables B0.1 and B0.2 show means and standard deviations for all bids (not only winning bids) by period for each treatment and asset rating. Generally, these statistics show little evidence of stabilization in bidding behavior with experience, as standard deviations remain similar in later periods compared to earlier periods. While the standard deviation of bids appears somewhat lower in later periods compared to early periods in some cases (such as F\$6 with uninformed banks), it is somewhat higher in later periods in other cases (such as N\$9.33 with uninformed banks). Overall, variation in bids does not appear to systematically trend either downward or upward with experience.

B.1. Winning bidder loss rates

Table B.1 summarizes the percentage of sequence periods 8-15 in which the winning bidder realized an ex post loss following the dividend realization. Loss rates are estimated via a linear probability estimate of instances where the winning bidder suffered a loss ex post in a period on indicator variable combinations that delineate disclosure condition/basic value realizations and bank information conditions. Formally, we estimate

$$loss_{gt} = \mathbf{D}\beta + e_{gt} \tag{B.1}$$

Where $loss_{gt}$ is an indicator variable taking on a value of 1 when the winning bidder in group g realized an ex post loss in period t, 0 otherwise, and $\mathbf{D}$ is the same vector of indicator variable combinations used in E. (1) in the text to estimate winning bid deviations.

Table B0.1
Bid means and standard deviations by asset rating for informed banks across periods.

	N$9.33		P$6		P$11		F$6		F$9		F$13	
Period	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
1	7.48	3.83	6.34	2.45	9.82	1.96	6.26	2.28	10.20	3.25	11.99	2.39
2	7.50	3.14	6.10	1.40	10.03	2.55	7.01	4.16	9.04	3.01	12.37	2.07
3	7.91	2.92	6.69	2.90	10.43	2.01	5.89	2.26	10.42	1.63	12.95	2.14
4	7.78	3.16	5.89	1.64	10.73	2.82	5.94	1.07	9.08	2.42	11.81	3.47
5	7.86	3.11	5.16	1.95	10.40	2.48	6.10	2.82	8.28	3.14	12.59	1.80
6	7.98	3.37	4.73	2.15	10.28	2.21	5.30	2.38	9.21	1.50	11.55	2.19
7	8.12	3.21	5.33	2.21	10.00	1.89	4.80	2.16	9.02	3.47	12.53	1.77
8	7.74	3.24	5.36	1.89	9.71	1.97	5.81	2.28	9.63	2.37	11.74	3.51
9	8.07	3.03	5.79	1.83	10.07	2.48	4.58	1.65	9.69	1.81	11.11	4.33
10	8.19	3.39	6.03	3.04	9.62	2.47	4.51	1.94	9.52	2.61	11.00	2.31
11	7.79	3.35	5.65	1.79	9.32	3.16	7.30	2.11	8.38	2.98	11.83	1.85
12	7.75	3.39	4.71	2.37	9.60	2.24	6.27	1.13	8.45	2.52	11.07	3.70
13	7.89	3.13	5.59	2.12	9.00	3.55	5.12	2.27	9.28	2.53	8.95	5.41
14	7.68	3.31	4.38	2.10	9.66	2.63	3.74	2.31	8.56	2.55	13.09	2.16
15	7.35	3.48	5.24	2.19	9.89	2.53	4.35	2.28	8.17	4.54	12.79	2.47

Table B0.2
Bid means and standard deviations by asset rating for uninformed banks across periods.

	N$9.33		P$6		P$11		F$6		F$9		F$13	
Period	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
1	8.07	2.79	5.62	2.92	10.21	1.75	6.67	2.40	9.99	1.89	10.70	2.77
2	7.75	2.87	5.36	1.82	9.57	3.15	6.92	3.06	8.87	3.41	12.28	2.60
3	8.50	2.44	6.01	3.36	10.35	2.76	6.62	3.26	8.71	1.65	12.23	2.92
4	7.78	2.48	6.69	3.27	9.23	3.15	5.11	2.38	10.20	1.75	11.53	4.48
5	8.00	3.18	4.94	1.37	10.73	3.43	5.32	2.42	8.92	2.37	12.70	2.33
6	8.11	2.34	6.32	2.53	8.74	4.79	3.83	2.45	8.30	1.78	12.33	2.62
7	7.92	2.93	6.30	2.90	11.23	2.70	4.93	2.46	9.42	2.22	12.95	1.80
8	7.93	2.53	5.95	1.97	10.44	3.22	4.83	2.32	9.52	2.21	11.00	3.24
9	8.35	2.41	5.92	1.35	10.09	2.80	3.83	2.67	9.18	1.75	11.00	3.10
10	8.41	2.42	5.57	2.60	10.83	2.19	6.41	2.45	7.60	1.40	11.67	4.07
11	8.30	2.83	6.09	1.37	10.39	2.64	4.86	2.23	11.06	3.21	10.63	4.10
12	8.20	3.07	5.23	2.45	11.17	2.90	4.85	1.99	8.26	2.39	12.33	2.21
13	8.06	3.05	6.00	1.00	10.31	2.70	5.19	2.24	9.50	2.15	13.63	2.22
14	8.42	3.47	5.33	2.78	9.64	3.15	4.12	2.33	7.82	3.09	11.66	2.59
15	8.69	3.42	5.62	2.14	10.71	2.03	4.43	1.79	8.70	2.39	11.52	4.04

Table B1
Winning bidder loss rates from sales last 8 periods of each sequence.

Bank Information	Disclosure Regime/Basic Value					
	f$6	*p*$6	*f*$9	*n*$9.33	*p*$11	*f*$13
Uninformed	42.9%**	29.8%**	40.9%**	38.3%**	49.3%**	48.8%**
Informed	35.7%**	20.0%**	50.0%**	39.8%**	41.0%**	47.6%**
		Differences Across Bank Information Conditions				
	7.1%	9.8%	-9.1%	-1.5%	8.4%	1.2%

Key: Entries reflect the percentage of periods where the winning bidder realized an ex post loss. *, ** reject H_o that the loss incidence does not differ from zero, $p<0.05$ and 00.1, respectively. °, °° reject H_o that the provision of basic value information to banks does not affect loss incidences $p<0.05$ and 00.1, respectively.

B.2. Myopic, regret-based bid adjustments leading to market volatility

Some insight into both the volatility of winning bids and the propensity for those bids to exceed the asset's expected value can be gained from a simple behavioral model of bidding, that assesses the impact of the most recent previous auction for a given asset value realization/ disclosure condition ('the last pertinent period') on subsequent bids. We also study the effects of ex-post regret on buyer bid adjustments, where 'regret' emanates both from submitting a losing bid when the final asset value in the last pertinent period happens to be high, as well as from submitting a winning bid when the asset realization turns out to be low. Results of this analysis suggest that bid volatility is in large part driven by a myopic response to the idiosyncratic dividend realization in the last pertinent period, and the propensity for overbidding is driven by ex-post regret.

To assess the impact of bidders' decisions in the last pertinent period on their bids, we regress the deviation of a buyer's bid from an asset's expected value as well as the realized ex post dividend, on a signed adjustment of the buyer's bid. Specifically, we estimate

$$Y_{it} - Y_{it'} = \alpha + \beta_{Lag\_y} y_{it'} + \beta_{Lag\_Div} Div_{it'} + \gamma' D + u_i + e_{it} \qquad (B.2)$$

The dependent variable $Y_{it} - Y_{it'}$ is the difference between Y_{it}, buyer i's bid in period t and $Y_{it'}$, the same buyer's bid in the most recent previous period (t'), where she observed an asset with the

Table B2
Bid adjustment regression estimates.

	All Bids	Lagged Overbids Only
β_{Lag_y}	-0.61**	-0.731**
	(0.039)	(0.055)
β_{Lag_Div}	0.061**	0.044
	(0.017)	(0.036)
$\beta_{L_{BLoss}}$		-0.935**
		(0.29)
$\beta_{L_{FPro}}$		0.404*
		(0.16)
$\beta_{L_{FLoss}}$		0.216
		(0.25)
constant	-0.81**	-0.016
	(0.13)	(0.18)
N (observations)	3723	1381
N (bidders)	93	86
N (groups)	31	31
R^2	0.227	0.291

Key: *, ** reject H_o that the coefficient does not equal 0, at $p < 0.05$ and 0.01 respectively

same rating. The primary independent variables are $y_{it\prime}$ the deviation of buyer *i*'s bid in the last realization of an asset from its expected value and $Div_{it\prime}$ the idiosyncratic dividend realized on that asset in period $t\prime$. Additionally, D is a vector of control variables that distinguish the different value realization/disclosure conditions as well as individual-specific fixed effects. To be conservative, we also cluster standard errors at the group level.

Regression results are summarized in the leftmost column of Table B.2. The large and significantly negative coefficient $\beta_{Lag\_y} = -0.61$ on the lagged bid deviation is fully rational, and was expected. A sizable overbid, for example is likely to result in losses, which will prompt lower bids. Similarly, a sizable underbid will leave a buyer unselected, to which the buyer would rationally respond with a bid increase.

More surprising, however, is the significant positive coefficient $\beta_{Lag\_Div} = 0.061$ on the lagged value of the dividend. This adjustment reflects a myopic buyer response to the idiosyncratic dividend realization, and cannot be rational. Altering one's bid in response to systemic factors, such as learning about the strategies of other bidders, may improve earnings. However, adjusting the current period's bid in response to an independently drawn random variable realization cannot predictably generate the same positive effect, because the dividend realization in the present period is as likely to deviate in the opposite direction as in the same direction of the last deviation. Moreover, we observe that the magnitude of myopic response may in some periods be quite large because the dividend may vary by as much as e\$5.00 in either direction of the expected value of zero. Thus, the 0.061 coefficient implies that large dividend realizations may affect the bid adjustment as much as e\$0.305, fully half the size of the rational adjustment. This adjustment in response to the previous period's dividend realization can drive persistent bid variability. Large positive dividend realizations in the last pertinent period drive bids further above an assets basic value, while large negative deviations have just the opposite effect.

Although a myopic response to the previous period's dividend may drive bid variability, it does not, by itself explain overbidding. For this, we explore the related concept of ex post regret. Regret may take form of *loss regret*, which would occur when the bidder wins the auction but ends up realizing a loss when the final dividend value is determined, and *foregone profits regret* that occurs in periods where the bidder fails to submit a bid high enough to win the last pertinent period's auction but, upon seeing the final asset value, realizes that she could have earned a profit had she submitted a higher bid.[27] Finally, although not really regret in the usual sense of the word, a bidder attending to results in the last pertinent period may also exhibit *foregone loss regret* by tempering overbidding if she observed that she avoided a loss by not winning the last pertinent period's auction.

To assess the impacts of regret, we evaluate a variant of the Eq. (B.1) that includes coefficients to capture loss regret, foregone profit regret and foregone loss regret. Also, in order to distinguish rational from non-rational responses, we restrict observations to instances in which buyers overbid in the last pertinent period.[28] Specifically, we estimate

$$Y_{it} - Y_{it\prime} = \alpha + \beta_{L_{Div}} Div_{it\prime} + \beta_{L_y} y_{it\prime} + \beta_{L_{BLoss}} D_{\mathrm{BuyLoss}\ t\prime} + \beta_{L_{FPro}} D_{\mathrm{ForgoProfit}\ t\prime} + \beta_{L_{FLoss}} D_{\mathrm{ForgoLoss}\ t\prime} + \gamma' D + u_i + e_{it} \tag{B.3}$$

Eq. (B.3) supplements the independent variables previously included in B.3 with three additional indicator variables: $D_{BuyLoss\ t\prime}$ takes on a value of 1 if the bidder won the auction and made a sale in the last pertinent auction but realized a loss, 0 otherwise; $D_{ForgoProfit\ t\prime}$ takes on a value of 1 if the bidder did not make a sale in the last pertinent auction, but would have realized a profit had she completed a sale at the winning bid, 0 otherwise; and $D_{ForgoLoss\ t\prime}$, takes on a value of 1 the buyer did not win the auction, but would have suffered a loss had they won the auction, 0 otherwise. Given these three variables, the omitted condition corresponds to having won the last pertinent auction at a profit.

Results of this second regression are shown in the rightmost column of Table B.2. The large and significant $\beta_{L_{BLoss}} = -0.93$ coefficient is rational and was fully expected. In response to realizing a loss after overbidding to win an auction in the last pertinent period, bidders adjust their bids downward by an average amount of e\$0.93 more than the omitted condition (of winning the auction at a profit in the last previous period at a profit).

The positive and significant $\beta_{L_{FPro}} = 0.40$ coefficient, however, is less consistent with rationality. This coefficient indicates that each time an overbidding buyer lost the auction in the last pertinent period but then learns that she could have realized a profit had she submitted the higher winning bid, raises her bid by e\$0.40 over what she would have bid had she won last pertinent auction at a profit – an effect that cannot be rational because buyers significantly increase their bids *even though* they were already overbidding. In this way, foregone profits can drive persistent overbidding.[29]

Taken together these results suggest that myopic responses to the outcome of the last pertinent period may explain both bid volatility and a propensity for winning bids to exceed the asset's expected value.

[27] At the end of each period, bidders learn whether or not they won the auction as well as the asset's final value, which allows for a calculation of regret when the bidder does not win the auction (or no sale occurs).

[28] Consideration of responses to all previous pertinent periods would make it impossible to distinguish rational from myopic responses. A risk neutral bidder experiencing foregone profit regret, for example, would rationally raise her bid if she bid less than the asset's expected value in the last pertinent period. Raising an overbid in response to a foregone profit, however, cannot be rational. Similarly, a bidder may rationally reduce her overbid in response to winning the last pertinent auction at a loss, but reducing her bid would not be rational if her previous bid was below the asset's expected value.

[29] We also note that there is no corresponding 'foregone loss' effect, which we might expect to be negative in light of the positive and significant regret from 'foregone profits'. In fact, although $\beta_{L_{FLoss}}$ does not differ significantly from zero, it is positive. Evidently, having avoided a loss in the last pertinent period does nothing to promote increased caution.

Table B3.1
Mean deviations of winning bids from equilibrium predictions with banks informed about basic values.

Periods Used for Estimate	Ratings Scheme/Expected Value F$6	P$6	F$9	N$9.33	P$11	F$13
All	1.19**	1.14**	2.02**	0.52	0.45	0.53
	(0.35)	(0.30)	(0.46)	(0.51)	(0.23)	(0.45)
Last 10	0.60	0.92**	1.92**	0.60	0.21	0.26
	(0.28)	(0.27)	(0.43)	(0.49)	(0.24)	(0.53)
Last 8	0.55	1.00**	1.87**	0.55	0.12	0.30
	(0.30)	(0.28)	(0.44)	(0.47)	(0.24)	(0.58)
Last 5	0.51	0.80**	1.85**	0.53	0.03	0.39
	(0.32)	(0.27)	(0.50)	(0.48)	(0.31)	(0.62)
	Differences in Means					
All – Last 8	0.64	0.14	0.15	-0.03	0.33	0.23
Last 10 – Last 8	0.05	-0.08	0.05	0.05	0.09	-0.04
Last 5 – Last 8	-0.04	-0.20	-0.02	-0.02	-0.09	0.09

Key: *, ** reject H_o that the winning bid does not deviate significantly from zero $p<0.05$ and 0.01, respectively. °, °° reject H_o that the provision of basic value information to banks does not affect winning bid deviations at $p<$ 0.05 and 0.01, respectively.

Table B3.2
Mean deviations of winning bids from equilibrium predictions with banks uninformed about basic values.

Periods Used for Estimate	Ratings Scheme/Expected Value F$6	P$6	F$9	N$9.33	P$11	F$13
All	1.34*	1.72**	1.83**	0.88**	1.06*	0.87
	(0.49)	(0.43)	(0.43)	(0.40)	(0.39)	(0.45)
Last 10	0.72	1.66**	1.80**	0.91	1.17**	0.84
	(0.52)	(0.38)	(0.50)	(0.43)	(0.35)	(0.52)
Last 8	0.72	1.33**	1.92**	1.03*	1.11**	0.85
	(0.55)	(0.34)	(0.49)	(0.45)	(0.35)	(0.54)
Last 5	0.62	1.47**	2.17**	1.31*	1.00*	0.85
	(0.54)	(0.40)	(0.57)	(0.51)	(0.35)	(0.57)
	Differences in Means					
All – Last 8	0.62	0.39	-0.09	-0.15	-0.05	0.02
Last 10 – Last 8	0	0.33	-0.12	-0.12	0.06	-0.01
Last 5 – Last 8	-0.10	0.14	0.25	0.28	0.11	0.00
Periods Used for Estimate	Differences Across Bank Information Conditions					
All	-0.15	-0.58	0.19	-0.36	-0.61	-0.34
Last 10	-0.12	-0.74	0.12	-0.31	**-0.96****	-0.58
Last 8	-0.17	-0.33	-0.05	-0.48	**-0.99****	-0.55
Last 5	-0.11	-0.67	-0.32	-0.78	**-0.97***	-0.46

Key: *, ** reject H_o that the winning bid does not deviate significantly from zero $p<0.05$ and 0.01, respectively. °, °° reject H_o that the provision of basic value information to banks does not affect winning bid deviations at $p<0.05$ and 0.01, respectively.

B.3. Mean winning bid deviations

Tables B3.1 and B3.2 report the mean deviations of winning bids from equilibrium predictions for Basic Value Informed and Basic Value Uninformed banks, respectively. These tables complement Table 3 in the text by supplementing the deviation estimates for the last 8 sequence periods reported in the text with comparable estimates using all periods, the last 10 periods, and the last 5 periods of each sequence as the basis of analysis. Comparing the mean winning bid deviations across the different specifications provides a robustness check for the results reported in Table 3. As can be seen in Tables B3.1 and B3.2, estimates based on each of the alternative sequence periods subsets used as the basis of analysis robustly support both Findings 1 and 2. As Finding 1 states, winning bids are highly variable (as indicated by large standard deviations) and for many ratings scheme/disclosure conditions differ significantly from 0, as stated in Finding 1. With one minor exception, each of the significant differences identified using the last 8 periods as the basis of analysis are also significant using each of the other choices of sequence periods as the basis of analysis (The single difference is for the P$6 condition in the informed bank condition. As shown in Table B3.1 the estimated deviation misses significance when using the last 5 sequence periods as the basis of analysis.)

As can also be seen in the comparisons across bank information conditions, shown at the bottom of Table B3.2, with one exception changes in the banks' information condition significantly affect bids only in the $11 realization of the partial disclosure condition. (The single difference is the specification based on all sequence periods, where the mean difference across bank information in the P$11 condition is not significant.)

Finally, while mean winning bid estimates based on the last 10, the last 8 and the last 5 periods of each sequence tend to be quite similar, examination of the differences between the estimates based on all periods and those based on the final 8 periods of each sequence differ by more sizable margins in several instances, suggesting some adjustment effects in initial sequence periods. In particular, notice in Table B3.1 that for value informed banks, mean winning bids fell by 64 cents in the F$6 conditions and by 33 cents in the P$11 condition. Again, for value uninformed banks Table B3.2, across the All – Last 8 period comparisons mean winning bids fell by 62 cents in the F$6 condition and by 39 cents in the P$6 condition. In both tables mean winning bid estimates differed by more than 30 cents in only one other instance (33 cents for the P$6 condition in the Last 10 - Last 8 comparison).

Table B4.1
Sales probabilities means (Std. Deviations) informed banks, real bidders.

	Expected Basic Value/Relevant Price Range					
Periods Used for Estimate	*a*	*b*	*c*	*d*	*e*	*f*
All	0.18^{b}	0.49^{**}	$0.85^{\dagger\dagger bb}$	0.06^{ee}	$0.59^{\dagger\dagger}$	$0.81^{\dagger\dagger e}$
	(0.12)	(0.04)	(0.04)	(0.04)	(0.09)	(0.07)
Last	0.17^{b}	0.52^{**}	$0.84^{\dagger\dagger bb}$	0.10^{ee}	$0.59^{\dagger\dagger}$	0.81
10	(0.12)	(0.04)	(0.04)	(0.07)	(0.09)	(0.10)
Last	0.18^{bb}	0.56^{**}	$0.86^{\dagger\dagger bb}$	0.12^{ee}	$0.64^{\dagger\dagger}$	0.79
8	(0.12)	(0.06)	(0.04)	(0.08)	(0.10)	(0.10)
Last	0.17^{b}	0.53^{**}	$0.84^{\dagger bb}$	0.20^{ee}	$0.67^{\dagger\dagger}$	0.84
5	(0.08)	(0.07)	(0.06)	(0.13)	(0.09)	(0.07)
Differences (Means)						
All - Last 8	0	-0.07	-0.01	-0.06	-0.05	0.02
Last 10 - Last 8	-0.01	-0.04	-0.02	-0.02	-0.05	0.02
Last 5 - Last 8	-0.01	-0.03	-0.02	0.08	0.03	0.05

Key: $^{*, **}$ reject H_o that the probability of a sale does not deviate significantly from zero $p<0.05$ and 0.01, respectively (for *a, b* and *d* only). †,†† reject H_o that the probability of a sale does not differ from 1 at $p<0.05$ and 0.01, respectively (for *c, e* and *f* only). $^{b,\ bb}$ reject H_o that the probability of a sale does not differ from that observed for basic value/winning bids that fall in area *b* (for areas *a* and *c* only). $^{e,\ ee,}$ reject H_o that the probability of a sale does not differ from that observed for basic value/winning bids that fall in area *e* (for areas *d* and *f* only).

Table B4.2
Sales probabilities means (Std. Deviations) uninformed banks, real bidders.

	Expected Basic Value/Relevant Price Range					
Periods Used for Estimate	*a*	*b*	*c*	*d*	*e*	*f*
All	0.24^{**bb}	0.50^{**}	$0.87^{\dagger\dagger bb}$	0.67^{*}	$0.76^{\dagger}$	$0.91^{\dagger}$
	(0.06)	(0.08)	(0.03)	(0.28)	(0.12)	(0.05)
Last	0.25^{**}	0.46^{**}	$0.87^{\dagger\dagger bb}$	–	$0.74^{\dagger}$	0.91
10	(0.06)	(0.07)	(0.03)		(0.11)	(0.06)
Last	0.33^{**}	0.47^{**ee}	$0.90^{\dagger\dagger bb}$	–	$0.73^{\dagger}$	0.91
8	(0.06)	(0.08)	(0.03)		(0.10)	(0.05)
Last	0.40^{*}	0.50^{**}	$0.90^{\dagger\dagger bb}$	–	$0.75^{\dagger}$	0.91
5	(0.14)	(0.09)	(0.03)		(0.09)	(0.05)
Differences (Means)						
All - Last 8	-0.09	0.03	-0.03	0.67	0.03	0
Last 10 - Last 8	-0.08	-0.01	-0.03	–	0.01	0
Last 5 - Last 8	0.07	0.03	0	–	0.02	0

Key: $^{*, **}$ reject H_o that the probability of a sale does not deviate significantly from zero $p<0.05$ and 0.01, respectively (for *a, b* and *d* only). †,†† reject H_o that the probability of a sale does not differ from 1 at $p<0.05$ and 0.01, respectively (for *c, e* and *f* only). $^{b,\ bb}$ reject H_o that the probability of a sale does not differ from that observed for basic value/winning bids that fall in area *b* (for areas *a* and *c* only). $^{e,\ ee}$ reject H_o that the probability of a sale does not differ from that observed for basic value/winning bids that fall in area *e* (for areas *b, d* and *f* only).

B.4. Sales probability estimates

Tables B4.1–B4.4 report linear probability estimates of sales probabilities for expected basic value/price ranges a – f. These tables complement Table 4 in the text by supplementing the deviation estimates based on the last 8 sequence periods (as reported in the text) with comparable estimates using all periods, the last 10 periods, and the last 5 periods of each sequence as the basis of analysis, in this way providing a robustness check for the results reported in Table 4. As can be seen by comparing instances where sales probabilities for an expected basic value/price range differ significantly from 0 (indicated by *'s) or 1 (indicated by '†'s), and differ significantly across ranges (indicated by '^{b}'s and '^{e}'s), with incidental exceptions each of the significant comparisons based on estimates using the last 8 sequence periods remain significant when using any of the other sequence period subsets. Thus, Finding 3 holds regardless of the sequence period subset used as the basis of analysis: banks sell with significantly higher frequencies when the winning bid exceeds the minimum acceptable price (e.g., areas *c*, *e* and *f*) than not (areas *a*, *b*, and *d*). Nevertheless, sales deviations deviate substantially from predictions, particularly when the winning bid falls between the minimum acceptable price and

Table B4.3
Sales probabilities means (Std. Deviations) informed banks, automated bidders.

	Expected Basic Value/Relevant Price Range					
Periods Used for Estimate	*a*	*b*	*c*	*d*	*e*	*f*
All	–	0.33^{**e}	–	–	$0.57^{\dagger\dagger}$	–
		(0.04)			(0.06)	
Last	–	0.31^{**e}	–	–	$0.54^{\dagger\dagger}$	–
10		(0.04)			(0.07)	
Last	–	0.32^{**e}	–	–	$0.52^{\dagger\dagger}$	–
8		(0.04)			(0.07)	
Last	–	0.36^{**}	–	–	$0.52^{\dagger\dagger}$	
5		(0.04)			(0.07)	
Differences (Means)						
All - Last 8	–	0.01	–	–	0.05	–
Last 10 - Last 8	–	-0.01	–	–	0.02	–
Last 5 - Last 8	–	0.04	–	–	0	–

Key: $^{*, **}$ reject H_o that the probability of a sale does not deviate significantly from zero $p<0.05$ and 0.01, respectively (for *a, b* and *d* only). †,†† reject H_o that the probability of a sale does not differ from 1 at $p<0.05$ and 0.01, respectively (for *c, e* and *f* only). $^{b,\ bb}$ reject H_o that the probability of a sale does not differ from that observed for basic value/winning bids that fall in area *b* (for areas *a* and *c* only). $^{e,\ ee}$ reject H_o that the probability of a sale does not differ from that observed for basic value/winning bids that fall in area *e* (for areas *b, d* and *f* only).

Table B4.4
Sales probabilities means (Std. Deviations) uninformed banks, automated bidders.

Periods Used for Estimate	Expected Basic Value/Relevant Price Range					
	a	*b*	*c*	*d*	*e*	*f*
All	–	0.33^{**e}	–	–	$0.57^{\dagger\dagger}$	–
		(0.04)			(0.09)	
Last	–	0.35^{**}	–	–	$0.53^{\dagger\dagger}$	–
10		(0.05)			(0.10)	
Last	–	0.35^{**}	–	–	$0.54^{\dagger\dagger}$	–
8		(0.05)			(0.10)	
Last	–	0.34^{**}	–	–	$0.52^{\dagger\dagger}$	–
5		(0.06)			(0.10)	
Differences (Means)						
All - Last 8	–	-0.02	–	–	0.03	–
Last 10 - Last 8	–	0	–	–	-0.01	–
Last 5 - Last 8	–	-0.01	–	–	-0.02	–

Key: $^{*,\,**}$ reject H_o that the probability of a sale does not deviate significantly from zero $p<0.05$ and 0.01, respectively (for *a*, *b* and *d* only). †,†† reject H_o that the probability of a sale does not differ from 1 at $p<0.05$ and 0.01, respectively (for *c*, *e* and *f* only). $^{b,\,bb}$ reject H_o that the probability of a sale does not differ from that observed for basic value/winning bids that fall in area *b* (for areas *a* and *c* only). $^{e,\,ee}$ reject H_o that the probability of a sale does not differ from that observed for basic value/winning bids that fall in area *e* (for areas *b*, *d* and *f* only).

the bonus cutoff (e.g., areas *b* - where sales should be never occur - and area *e*, where sales should always occur).

As was the case for the mean winning bid estimates summarized in Appendix B3.1, one of the All – Last 8 differences is large and suggests some initial adjustment. In the real buyer treatment with value uninformed banks shown in Table B4.2 the mean winning bid fell by 67 percentage points in expected value/price range *d* when comparing estimates based on all periods of each sequence rather than estimates based on the last 8 periods. This large difference is driven by a very limited number of instances of observations in range *d*, but nevertheless suggests some initial adjustment effects for which estimates based on a truncation of the sequence periods control.

B.5. Bonus incidence estimates

Tables B5.1–B5.4 report linear probability estimates using the variants of estimating Eq. (3) described in Section 3.3 of the text, but varying the number of sequence periods used for the estimation from the last 8 sequence periods reported in the text to consider all periods, the last 10 periods, and the last 5 periods. Looking

Table B5.1
Bonus incidences, means (Std. Deviations). informed banks, real bidders.

Periods Used for Estimate	Disclosure Regime		
	None	Partial	Full
All	$0.69^{**\dagger\dagger}$	$0.62^{**\dagger}$	$0.62^{**\dagger}$
	(0.07)	(0.03)	(0.05)
Last 10	$0.69^{**\dagger\dagger}$	$0.59^{*\dagger}$	$0.62^{*\dagger}$
	(0.07)	(0.04)	(0.06)
Last 8	$0.69^{**\dagger\dagger}$	$0.57^{**\dagger\dagger}$	$0.63^{**\dagger}$
	(0.07)	(0.04)	(0.06)
Last 5	$0.67^{**\dagger\dagger}$	$0.52^{\dagger\dagger}$	0.64^{*}
	(0.07)	(0.04)	(0.06)
Differences (Means)			
All - Last 8	0	-0.05	0.01
Last 10 - Last 8	0	-0.02	0.01
Last 5 - Last 8	-0.02	-0.05	0.01

Key: $^{*,\,**}$ reject H_o that the mean bonus incidence does not deviate from the no trade prediction at $p<0.05$ andv 0.01, respectively. †,†† reject H_o that the mean bonus incidence does not deviate from the optimal prediction at $p<0.05$ and 0.01, respectively. ^{aa} reject H_o that the mean price does not differ across no disclosure and partial disclosure conditions $p<.01$; ^{bb} reject H_o that the mean price does not differ across partial and full disclosure conditions, $p<.01$.

Table B5.2
Bonus incidences, means (Std. Deviations). Uninformed banks, real bidders.

Periods Used for Estimate	Disclosure Regime		
	None	Partial	Full
All	$0.69^{**\dagger\dagger}$	$0.61^{**\dagger\dagger}$	$0.64^{**\dagger\dagger}$
	(0.06)	(0.03)	(0.04)
Last	$0.68^{**\dagger\dagger}$	$0.61^{**\dagger}$	0.64^{**}
10	(0.07)	(0.03)	(0.05)
Last	$0.69^{**\dagger\dagger}$	0.64^{**}	$0.62^{**\dagger}$
8	(0.08)	(0.04)	(0.06)
Last	$0.70^{**\dagger\dagger}$	0.68^{**}	$0.59^{*\dagger}$
5	(0.07)	(0.05)	(0.06)
Differences (Means)			
All - Last 8	0	0.03	-0.02
Last 10 - Last 8	0.01	0.03	-0.02
Last 5 - Last 8	0.01	0.04	-0.03

Key: $^{*,\,**}$ reject H_o that the mean bonus incidence does not deviate from the no trade prediction at $p<0.05$ and 0.01, respectively. †,†† reject H_o that the mean bonus incidence does not deviate from the optimal prediction at $p<0.05$ and 0.01, respectively. ^{aa} reject H_o that the mean price does not differ across no disclosure and partial disclosure conditions $p<.01$; ^{bb} reject H_o that the mean price does not differ across partial and full disclosure conditions, $p<.01$.

Table B5.3
Bonus incidences, means (Std. Deviations). Informed banks, automated bidders.

Periods Used for Estimate	Disclosure Regime		
	None	Partial	Full
All	0.29^{**aa}	$0.62^{**\dagger\dagger}$	$0.41^{bb\dagger}$
	(0.02)	(0.02)	(0.03)
Last	0.32^{**aa}	$0.61^{**\dagger}$	$0.41^{bb\dagger\dagger}$
10	(0.03)	(0.03)	(0.03)
Last	0.36^{aa}	$0.58^{**\dagger\dagger}$	0.44^{bb}
8	(0.04)	(0.04)	(0.03)
Last	0.38^{aa}	0.61^{**}	0.45^{bb}
5	(0.05)	(0.04)	(0.04)
Differences (Means)			
All - Last 8	0.07	-0.04	0.03
Last 10 - Last 8	0.04	-0.03	0.03
Last 5 - Last 8	0.02	0.03	0.01

Key: $^{*,\,**}$ reject H_o that the mean bonus incidence does not deviate from the no trade prediction at $p<0.05$ and 0.01, respectively. $^{\dagger,\,\dagger\dagger}$ reject H_o that the mean bonus incidence does not deviate from the optimal prediction at $p<0.05$ and 0.01, respectively. ^{aa} reject H_o that the mean price does not differ across no disclosure and partial disclosure conditions $p<.01$; ^{bb} reject H_o that the mean price does not differ across partial and full disclosure conditions, $p<0.01$.

over the entries showing the differences in bonus incidences using a different number of sequence periods as the basis of analysis from the last 8 periods reported in the text, note that variations in the number of periods used for estimates changed the mean bonus incidence by more than 5 percentage points in only once instance: As shown in Table B5.3, in the automated bidder treatment with value informed banks using all sequence periods as the basis for analysis, rather than the last 8 sequence periods results in a bonus incidence that is 7 percentage points lower than the 36 percent incidence reported in the text. Variations in the periods used as the basis of analysis did not change the standard deviation of the bonus incidence estimates by more than 2 percentage points.

More importantly, notice from the superscripted ^{a} and ^{b} entries that appear in the columns summarizing the ‘None’ and ‘Full’ information Disclosure regimes for the automated bidder treatments, but that do not appear in the comparable columns for the real bidder treatments, Finding 4 holds regardless of the segment of sequence periods used as the basis of analysis: with bidders auto-

Table B5.4
Bonus incidences, means (Std. Deviations). Uninformed banks, automated bidders.

Periods Used for Estimate	Disclosure Regime None	Partial	Full
All	0.32*†aa	0.60**†	0.36††bb
	(0.04)	(0.04)	(0.04)
Last 10	0.30*†aa	0.59**†	0.34††bb
	(0.05)	(0.05)	(0.04)
Last 8	0.33*†aa	0.62**	0.34††bb
	(0.04)	(0.05)	(0.05)
Last 5	0.33*†aa	0.62**	0.34††bb
	(0.04)	(0.05)	(0.05)
Differences (Means)			
All - Last 8	0.01	0.02	-0.02
Last 10 - Last 8	0.03	0.03	0
Last 5 - Last 8	0	0	0

Key: *, ** reject H_o that the mean bonus incidence does not deviate from the no trade prediction at p<0.05 and 0.01, respectively. †, †† reject H_o that the mean bonus incidence does not deviate from the optimal prediction at p<0.05 and 0.01, respectively. aa reject H_o that the mean price does not differ across no disclosure and partial disclosure conditions $p<.01$; bb reject H_o that the mean price does not differ across partial and full disclosure conditions, $p<0.10$.

mated to submit bids equal to expected values, bonus incidences are higher under partial disclosure than under either no disclosure or full disclosure.

Appendix C. Sample experiment instructions

The instructions listed below are for the real buyer sessions when traders ('banks') are value informed. When traders are not told their asset's basic value they are instead told that they know the same information as buyers. In the automated buyer sessions, traders are told that buyers are automated to pay a price equal to the asset's expected value, and then are shown a table that indicates buyer prices for each differ basic value/ disclosure condition. In all cases both the summary and the quiz questions at the end of the instructions were adjusted appropriately.

Overview: Welcome! Thank you for coming to today's session. This is an experiment in the economics of decision-making. Various foundations have provided funds for this research. The instructions are simple, and if you follow them carefully and make good decisions, you may earn a considerable amount of money that will be paid to you in CASH at the end of the experiment. Your earnings will be determined partly by your decisions, partly by chance and partly by the decisions of others.

General description

- Today's experiment consists of three sequences of 15 trading periods, for a total of 45 periods.
- In each period, three *buyers* and one *trader* meet.
  - *Buyers* are given initial cash each period that can be used to purchase an asset.
  - The *Trader* is given an asset whose value is uncertain. She decides whether to sell the asset or keep it.
- Cash and asset values are denominated in terms of Experimental Currency Units ('ECUs'). As with U.S. currency, ECU's can be traded in 'penny' (.01 ECU) increments. ECUs will be converted into U.S. currency at the end of the session.

Table C.1
Some possible final asset values.

Dividend	Basic Value (ECU) 6.00	9.00	13.00
-5.00	1.00	4.00	8.00
-4.00	2.00	5.00	9.00
-3.00	3.00	6.00	10.00
-2.00	4.00	7.00	11.00
-1.00	5.00	8.00	12.00
0.00	6.00	9.00	13.00
1.00	7.00	10.00	14.00
2.00	8.00	11.00	15.00
3.00	9.00	12.00	16.00
4.00	10.00	13.00	17.00
5.00	11.00	14.00	18.00

Asset value

- The total value of an asset will be determined as the sum of two elements, the basic value of the asset and the dividend:

  $$\text{Asset Value} = \text{Basic Value} + \text{Dividend}$$

  - Basic Value: The basic value of an asset will be randomly chosen from the set {6.00, 9.00, 13.00}. All basic draws are equally likely. Thus there is a 1/3 chance the basic value is 6.00, a 1/3 chance it is 9.00, and a 1/3 chance it is 13.00.
  - Dividend: The asset dividend will be a number randomly chosen from the range [-5, 5] in increments of 0.01 ECU, with each number being equally likely.
- Table C.1 lists some possible final asset value realizations. For example, with a basic value of 13.00, the final asset value may be as low as 8.00 and as high as 18.00. Similarly, with a basic value of 6.00, the final asset value may be as low as 1.00 and as high as 11.00.
  - Note: Table C.1 shows only sample values, since dividends are in 0.01 ECU increments.
  - Note also that although dividend outcomes may vary widely, since each outcome is equally likely the average dividend value is 0.
  - Note finally that the endpoints -5.00 and 5.00 each occur with a 1% probability, but the probability of a dividend outcome on any interval between the 1.00 dividend increments shown is 10%.

Information about the asset

- Neither the trader nor the buyers will know the dividend until the end of period.
- At the beginning of the period,
  - the trader will know the asset's basic value.
  - the buyers will not know the asset's basic value, but they will be given a rating of the asset's basic value.

Basic value rating systems

- Table C.2 describes three rating systems of basic value: Complete, Partial, and Uniform. In the complete rating system each basic value has its own rating, "High", "Medium", or "Low"; in the partial rating system, medium and high basic values are assigned the same "Medium/High" rating while the low basic value has a separate "Low" rating; in the uniform system all basic values have the same "Neutral" rating.

Table C.2
Ratings systems.

	Complete Ratings system	Partial Ratings system	Uniform Ratings system
Basic Value = 13.00	"High"	"Medium/High"	"Neutral"
Basic Value = 9.00	"Medium"	"Medium/High"	"Neutral"
Basic Value = 6.00	"Low"	"Low"	"Neutral"

- The rating system to be used in each sequence will be announced prior to the sequence's start, and will remain in effect for all 15 periods of the sequence.

Buyers

- At the beginning of each period each buyer is given 5.00 ECUs, plus an additional 10.00 ECU working capital loan which must be repaid at the periods' end. At the beginning of each period buyers are also shown a rating of the asset's basic value for that period.
- Buyers make a price offer for the trader's asset, with increments of 0.01 ECUs.
- The highest price offer becomes the offer price, and the buyer making the offer price will purchase the asset if the trader chooses to sell. In the case of a tied offer price, one of the tied buyers will be chosen randomly.
- Each buyer's earnings are determined as the sum of all remaining ECUs of the buyer plus the value of an asset if one was purchased minus the loan. In other words:
    - If the buyer purchased an asset, the buyer earns the value of the asset, plus their 15.00 ECU endowment minus the price paid for the asset, minus the 10.00 ECU loan.
    - If no asset was purchased, the buyer repays the 10.00 ECU loan from their 15.00 ECU endowment and earns 5.00 ECU.

$$\text{Buyer Earnings} = \begin{cases} 15.00 - \textit{price} + \textit{asset value} \ - 10.00 & \text{if asset purchased} \\ 15.00 - 10.00 & \text{if no asset purchased} \end{cases}$$

Traders

- At the beginning of each period, the trader is given one asset.
- Traders will be shown the basic value of the asset but not the dividend.
- The trader must decide whether to sell their asset at the highest price offered by buyers or keep it.
- The trader earns the offer price if she sells and the final asset value if she does not sell.
- Also, the trader earns an extra 15.00 ECU bonus if she sells the asset for at least 10.00 ECUs or if she keeps the asset and the value of the asset turns out to be at least 10.00 ECUs.
- Table C.3 shows some possible trader earnings if the trader keeps the asset. Notice the bolded entries, which emphasize the 15.00 ECU earnings bonus whenever the Final Asset value is 10.00 ECUs or more. For example, given a basic value of 9.00, the asset could be worth as little as 4.00 or as much as 29.00 (14.00 + 15.00 Bonus).
- *If the trader sells the asset for 10.00 ECU or more, the trader can guarantee the 15.00 ECU bonus added to the price of the asset.*
- Finally, independent of whether or not the trader sold her asset, she must pay a 10.00 ECU trader tax at the end of each period

$$\text{Trader Earnings} = \begin{cases} \textit{price}\ (+\ 15.00\ \textit{if}\ \textit{price} \geq 10.00) - 10.00\ \textit{tax} & \text{if asset sold} \\ \textit{asset value}\ (+\ 15.00\ \textit{if}\ \textit{asset value} \geq 10.00) - 10.00\ \textit{tax} & \text{if asset kept} \end{cases}$$

Table C.3
Some possible trader earnings: If the final asset value is 10.00 ECU or more, the trader receives a 15.00 ECU bonus.

	Basic Value		
Dividend	6.00	9.00	13.00
-5.00	1.00	4.00	8.00
-4.00	2.00	5.00	9.00
-3.00	3.00	6.00	**25.00**
-2.00	4.00	7.00	**26.00**
-1.00	5.00	8.00	**27.00**
0.00	6.00	9.00	**28.00**
1.00	7.00	**25.00**	**29.00**
2.00	8.00	**26.00**	**30.00**
3.00	9.00	**27.00**	**31.00**
4.00	**25.00**	**28.00**	**32.00**
5.00	**26.00**	**29.00**	**33.00**

Additional procedures

- Each participant will be assigned the role of trader or buyer at the beginning of the experiment. You will remain in this role for the entirety of today's experiment.
- Three buyers and one trader will be matched into a group of four participants. You will remain in the same group with the same participants throughout today's experiment.
- The session will divided into three sequences. At the beginning of each sequence, the effective ratings system will be announced.
- You will be paid for the outcomes of decisions in each period of each sequence.
- The ECU that you earn in today's experiment will be converted to dollars at the rate of
  15.00 ECU = $1.00
- After the 3 sequences of trading periods, there will be a short questionnaire with an opportunity to earn more money.
- Your earnings for today are equal to the sum of your earnings in each of the three paying periods, plus the questionnaire earnings, plus a $5.00 show-up fee.
- You will be paid privately in cash at the end of the experiment.

Summary

- Three buyers and one trader trade an asset.
- Final Asset Value = Basic Value {6.00, 9.00, or 13.00} + the Dividend [between -5.00 and 5.00].
- No one knows the dividend at the time of trade.
- The trader knows the basic value. Buyers are given a rating of the basic value based on a complete, partial or uniform rating system, depending on the sequence. The rating system changes every 15 period sequence.
- The highest offer of the buyers is given to the trader, and she decides to sell or not.

- The buyer earns 15.00 – price + asset value – 10.00 if she buys and 5.00 if she does not buy.
- The trader earns price (plus 15.00 if price ≥ 10.00) – 10.00 if she sells and asset value (plus 15.00 if asset value ≥ 10.00) – 10.00 if she does not.

Quiz of understanding

Procedures

1 Each period, buyers and traders will be re-matched into different groups. (T or F)
2 The trader knows the basic value of the asset before trading it. (T or F)
3 The buyers do not know the asset's basic value but they do know its rating. (T or F)
4 Under Complete ratings, each possible basic value gets a unique rating. (T or F)
5 Under Partial ratings, each possible basic value gets a unique rating. (T or F)
6 Under Uniform ratings, each possible basic value gets a unique rating. (T or F)

Asset value

1 How much may the dividend vary? On average, what is the expected dividend value?
2 If an asset's basic value is 6.00, and the dividend is 4.21, what is the final asset value? What is this asset worth to a trader if she does not sell it? What is the probability of seeing a dividend above 4.00?
3 If an asset's basic value is 13.00, and the dividend is -3.01, what is the final asset value? What is the asset worth to a trader if she does not sell the asset? What is the probability of seeing a dividend below -3.00?
4 If an asset's basic value is 9.00 and the dividend is 0.99, what is what is the final asset value? What is this asset worth to the trader? What is the probability of seeing a dividend less than 1.00?

Earnings calculation

1 What are a buyer's earnings in a trading period if he buys an asset for 8.00, the asset's basic value is 9.00, and the dividend is 4.00?
2 What are a buyer's earnings in a trading period if he does not buy an asset?
3 What are a trader's earnings in a trading period if the she sells an asset for 12.50, the asset's basic value is 13.00 and the dividend is -4.50?
4 What are a trader's earnings in a trading period if she sells an asset for 8.00, the asset's basic value is 13.00 and the dividend is -4.50?
5 What are a trader's earnings in a trading period if she keeps an asset which has a basic value of 13.00 and the dividend is -4.50?

At the beginning of a complete ratings sequence

In the next 15 periods a complete ratings system will be in effect. In each period buyers will be told if the basic value of the trader's asset is 'High' (e.g., 13.00 ECUs), 'Medium' (9.00 ECU's) or 'Low' (6.00 ECU's). Traders will also know their asset's basic value. In light of their information, each buyer will enter a purchase price and then press ENTER. Once all prices are posted an offer price will be determined, and the Trader will make a sales decision. Finally the dividend will be determined and earnings calculated for all participants.

Buyers, please start period 1 by posting your purchase price now.

At the beginning of a partial ratings sequence

In the next 15 periods a partial ratings system will be in effect. In each period buyers will be told if the basic value of the trader's asset is 'Medium/High' (e.g., either 13.00 ECUs or 9.00 ECUs), or 'Low' (6.00 ECU's). Traders will know their asset's basic value. In light of their information, each buyer will enter a purchase price and then press ENTER. Once all prices are posted an offer price will be determined, and the Trader will make a sales decision. Finally the dividend will be determined and earnings calculated for all participants.

Buyers, please start period 1 by posting your purchase price now.

At the beginning of a neutral ratings sequence

In the next 15 periods a neutral ratings system will be in effect. All ratings are neutral so the buyers will not know the basic value of the asset. Traders, however, will know their asset's basic value. Buyers will enter a purchase price and then press ENTER. Once all prices are posted an offer price will be determined, and the trader will make a sales decision. Finally the dividend will be determined and earnings calculated for all participants.

Buyers, please start period 1 by posting your purchase price now.

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