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The Effect of Short Selling on Bubbles and Crashes in Experimental Spot Asset Markets

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ABSTRACT

A series of experiments illustrate that relaxing short-selling constraints lowers prices in experimental asset markets, but does not induce prices to track fundamentals. We argue that prices in experimental asset markets are influenced by restrictions on short-selling capacity and limits on the cash available for purchases. Restrictions on short sales in the form of cash reserve requirements and quantity limits on short positions behave in a similar manner. A simulation model, based on DeLong et al. (1990), generates average price patterns that are similar to the observed data.

ASSET MARKET BUBBLES ARE PERSISTENT DEVIATIONS of prices from fundamentals. To the extent that bubbles exist, they can influence investment levels and the allocation of capital, and thereby have considerable economic effects. In recognition of their potential importance, the question of the existence and pervasiveness of bubbles has been a focus of extensive empirical investigation (see, e.g., Shiller (1981), Blanchard and Watson (1982), Diba and Grossman (1988), and West (1988)). These studies yield mixed results regarding the empirical relevance of bubble phenomena. One source of the differences in conclusions may be that, because the fundamental value of the assets cannot be observed, tests of the presence of bubbles are joint tests, with the particular specification of the process guiding the evolution of fundamentals also being tested.

The availability of short selling is widely believed to make bubble formation less likely. One rationale for such a belief is the notion that the cause of asset market bubbles is a constraint on the ability of traders to speculate on future downward price movements (see, e.g., Miller (1977), Jarrow (1980), Diamond and Verrecchia (1987), or Figlewski and Webb (1993)). In the absence of short sales, traders may sell only the shares in their portfolios; the availability of short sales relaxes this constraint.

In this paper, we study empirically the effect of allowing short sales on both the incidence and magnitude of market bubbles. We choose a setting in which the fundamental value of the asset is clearly and unambiguously defined and known at all times, and bubbles typically occur, namely we use the experimental environment that Smith, Suchanek, and Williams (1988) introduce. While

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laboratory markets are much simpler in structure than asset markets in the field and thus studying them may not address some of the questions that are important to applied researchers, they do provide an arena in which certain hypotheses about market behavior can be subjected to empirical testing. The main hypotheses of interest here are whether short selling reduces prices relative to fundamental values and whether short selling renders prices more likely to track fundamentals. These hypotheses appear to be well suited for evaluation within an experimental environment. Deviations from fundamental values can be measured with precision and the institution of short selling can be introduced into and removed from an environment in which all other institutional details are held constant.

To consider the effect of short selling on bubbles, we extend the experimental design of Smith et al. (1988), who identify a class of laboratory asset markets in which asset price bubbles and crashes typically occur. An active experimental literature has consistently replicated the bubble phenomenon in this environment and shows that it is robust to a variety of changes in asset and market structure (see, e.g., King et al. (1993), Van Boening, Williams, and LeMaster (1993), Porter and Smith (1995), Fisher and Kelly (2000), Noussair, Robin, and Ruffieux (2001), Lei, Noussair, and Plott (2001), Ackert et al. (2001), Dufwenberg, Lindqvist, and Moore (2002)). In all of these studies, a market is created for a dividend-paying asset with a lifetime of a finite number of periods, and the asset structure is common knowledge. The typical empirical pattern observed is a price bubble, a sustained episode of high transaction volume at prices that greatly exceed the fundamental value, which is usually followed by a crash to prices close to fundamental values near the end of the asset's lifetime.

There are several reasons that we choose a market with this particular structure. First, it is known to produce bubbles in a large majority of trials, and the tendency toward bubble formation is robust to many environmental changes. This means that there is room for institutional changes, such as short selling, to reduce the incidence and magnitude of bubbles. Second, the existence of a substantial body of previous experimental work with similar markets permits us to compare and interpret our results within a sizable literature and to verify that our procedures generate similar outcomes when applied in the same environment. Third, despite the relative simplicity of the decision situation, the market dynamics include a variety of behaviors thought to accompany bubble formation more generally, such as speculation generated from heterogeneous expectations about future price movements (Smith (1994)), as well as nonspeculative biases (Lei et al. (2001)).[1]

[1] Early explanations of the bubble-and-crash phenomenon in experimental asset markets (Smith, Suchanek, and Williams (1988), Smith, (1994)) posit that a lack of common knowledge of rationality leads to heterogeneous expectations about future prices. Such an account of bubble formation does not require individual traders to exhibit biases in decision making, but rather only that it fails to be common knowledge that all traders are rational. However, Lei et al. (2001) show that in addition to having a tendency to speculate, some subjects make transactions that reflect

While our decision to structure our markets in a manner similar to previous studies offers the above advantages, the use of the same market rules as previous studies, in particular the continuous double auction market, with its dynamic and interacting trading behavior and intractably complex strategy space, is conducive to a focus on market-level, rather than individual, behavior. Therefore, like all previous studies in the experimental literature on bubbles, the analysis here concentrates for the most part on the market as a whole rather than on individual decisions. However, we depart from previous studies in that we classify individual traders into types and study the implications of their interactions on properties of market behavior and the market response to cash and short-sale constraints.

We argue that endowing traders with the ability to short sell sufficient quantities, without increasing the amount of cash available for purchases of shares, may alter the price dynamics in laboratory asset markets so that prices are typically below fundamental values. The relaxation of short-sale constraints, either in the form of limits on the size of total net short positions or in the form of lower cash reserve requirements, serves to lower prices, regardless of whether or not prices are below or above fundamental values. The more short-selling capacity that is available, the more prices fall. Moreover, short selling does not induce prices to track fundamentals. This suggests that the nature of the reduction in the magnitude of price bubbles that is induced by the availability of short selling is not indicative of a tendency to push prices toward fundamentals, but rather of a general tendency to lower prices. Thus, the phenomenon of bubbles and crashes in laboratory asset markets is not a consequence of a lack of a short-selling possibility, the appropriate institutional structure that permits speculation on downward price movements. The experimental markets remain inefficient in the sense that the asset price fails to reflect its fundamental value, and they retain many of the properties that are associated with bubbles in markets with no short sales: very high transaction volume, large swings in prices relative to fundamentals, and sustained trading activity at prices far from fundamentals. Simply adding short-selling capability does not appear to eliminate the trader behavior that underlies bubble formation.

Our results point to an interpretation of the effect of short selling on asset market bubbles that contrasts sharply with those drawn from the two previous experimental studies of the effect of short sales in similar environments. King et al. (1993) find that the ability to short sell has no effect on the incidence and magnitude of asset price bubbles, and conclude that the bubble phenomenon is robust to the institutional change of allowing short selling. Ackert et al. (2001) find that the ability to short sell leads to prices close to fundamental values. Ackert et al. conclude that short selling improves the ability of the pricing mechanism to reach fundamentals and thus that restrictions on

nonspeculative biases. Specifically, subjects are shown to trade excessively when the asset market is the only activity available. Furthermore, in markets in which speculation is impossible (where units cannot be traded more than once), subjects often make purchases at prices greater than the maximum possible dividend realization during the boom phase. In Section IV, we propose the notion of feedback trading, which provides a plausible structure for these errors in decision making.

short selling are undesirable. They write: "Allowing short selling enhances the pricing mechanism and allows traders to move prices to levels justified by fundamentals," and "Short selling provides an equilibrating force in the market." The principal methodological differences between our study and the two above studies are discussed in Section I.

Trading patterns suggest the presence of several types of agents that populate our markets. The presence of bubbles indicates the possible existence of "feedback" traders who buy and sell on momentum, demanding more asset when prices have been rising, and thereby inflating the bubble. The fact that the fundamental value is made salient to participants suggests that there may also exist some "passive" agents, who trade based on fundamentals, making purchases when prices are below fundamentals and sales when they are above. Finally, because deviations of prices from fundamentals offer opportunities to earn profits from speculation, the existence of "speculators," sophisticated agents who trade based on estimates of prices in the near future, also appears reasonable. These three types of agents, feedback, passive, and speculator, correspond to those assumed in a model of a three-period asset market developed by DeLong et al. (1990). Conducting simulations, they find that the behavior of interacting agents of these three types causes a bubble-and-crash pattern in their model. The behavior of the feedback trader imposes a plausible structure on the decision-making errors in experimental asset markets identified by Lei et al. (2001). In Section IV, we report the results of our own simulations, in which agents of the three types in the DeLong et al. model participate in an asset market with the precise parametric structure of each of the treatments of our experiment. As we describe in Section IV, we find that the simulations reproduce the most prominent patterns we observe in our data, including the principal differences between treatments. The interacting strategies of feedback, passive, and speculator traders provide a plausible explanation for the empirical patterns we observe.

In Section I, we review related background research and list our hypotheses. In Section II, we describe the design and procedures of the experiment, and in Section III we present the data. Section IV contains a description and results from the simulation exercise described above. In Section V, we summarize our findings.

I. Background

The experiment is designed specifically to evaluate two conjectures that have their origin in economic and financial theory. The first hypothesis is that the availability of short selling induces prices to track their fundamental values. In the absence of short sales, the ability to speculate on downward price movements is limited to the sale of all shares in a trader's portfolio. In a market in which traders have differing degrees of rationality, such as a laboratory market, the lack of short-selling capability might constrain the most rational traders, who might otherwise arbitrage away any differences from fundamental values, with an insufficient supply of shares to do so. If short sales were permitted, the constraint would be relaxed and prices might track fundamental values. The conjecture that short selling eliminates deviations from fundamental values is the first hypothesis evaluated in our study.

HYPOTHESIS 1: In the presence of sufficient short-selling capacity, prices track fundamental values.

The second conjecture is a weaker hypothesis that asserts that allowing short selling, which increases the supply of shares, would simply result in a lower equilibrium price. The conjecture does not require that prices track fundamental values. Such an effect requires no assumptions about rational expectations on the part of traders, but rather can simply reflect basic microeconomics as expressed in the principle of supply and demand. For example, short sales can influence supply and demand if there are heterogeneous beliefs about dividends. Theorists have argued that in the absence of the possibility of short sales and liquidity constraints, the equilibrium price of an asset has a lower bound at the most optimistic trader's estimate of the fundamental value (Harrison and Kreps (1978), Morris (1995, 1996)).[2] This price typically exceeds the objective fundamental value and can be interpreted as a bubble (this account allows but does not require speculation). Indeed, Fisher (1998) argues that heterogeneous beliefs about future dividends can account for the particular bubble-and-crash price patterns obtained in experimental asset markets. However, if traders are able to short sell sufficient quantities, the supply of shares can respond elastically to demand, and the estimate of the most optimistic trader no longer defines a lower bound on prices. Since the possibility of short selling increases the available supply of shares at any price, and does not have a direct effect on demand, the result would be a lower equilibrium transaction price. This conjecture is considered here as our second hypothesis.

HYPOTHESIS 2: The presence of short selling induces lower transaction prices compared to a market with similar parameters in which no short sales are permitted. As short-selling capacity increases, prices fall.

There are two previous experimental studies that explore the effect of short selling on asset market behavior. King et al. (1993) are the first to study the effect of short selling on asset market bubbles in the laboratory. They find that endowing traders with the ability to short sell does not reduce the incidence or the magnitude of asset market bubbles. However, two features of the implementation of short sales in King et al. (1993) may attenuate any downward effect on prices that the availability of short sales might have otherwise created. First, King et al. limit the short-sale capacity of each individual to a relatively small amount. Second, they do not require short sellers to pay the dividends on their outstanding units, which means that short sales create additional cash balances and wealth. Higher cash balances are associated with higher prices (Caginalp,

[2] The absence of liquidity constraints is necessary because the most optimistic trader must have the ability to purchase the entire stock of units in the market.

Porter, and Smith (2000); our data here will show that this last relation extends to markets in which short sales are permitted).

Ackert et al. (2001) obtain contrasting results. They study the effect of short sales in a more complex experiment with two interdependent asset markets that have different dividend structures.[3] Their design includes a belief elicitation phase at the beginning of each period that provides strong incentives for accurate prediction.[4] Their data indicate that short sales reduce prices to levels close to fundamental values. They conclude that the availability of short sales eliminates the bubble-and-crash phenomenon and induces prices to track fundamentals. However, their data are not inconsistent with the hypothesis that short selling merely reduces prices, and that the greater the short-selling capacity, the more prices decrease.

As we describe in more detail below, the main result we obtain in this paper is quite different from the Ackert et al. study. In contrast to their conclusion that prices track fundamental values, we find that prices are below fundamental values for most of the trading horizon. We argue here, by exogenously and systematically varying restrictions on short sales, that short selling reduces prices and that the more short selling that is possible, the more prices fall. The possibility of short sales does not induce pricing at fundamentals in general. With sufficient short-selling capacity, prolonged busts, which are sustained episodes of prices below fundamental values, often result.[5]

Support for Hypothesis 2 would indicate the existence of trader behaviors other than those exhibited in a rational expectations equilibrium, in which prices would track fundamental values regardless of the existence of short-selling capability. Support for Hypothesis 2 would mean that at least some agents use other behavioral rules to determine trading strategies. If relaxing constraints on the ability to sell units is shown to lower prices because it increases the supply of shares to the market, then it would lead to a conjecture that relaxing the restrictions on the ability to make purchases, which limit potential demand, would lead to higher prices. The only restriction on the ability to make purchases is the fact that cash balances cannot become negative. Thus,

[3] In the Ackert et al. experiment, there are two assets, a "standard" asset and a "lottery" asset. The existence of a second market, in conjunction with the availability of short selling, creates a liquidity motive for short sales that does not exist in either our design or King et al. (1993). For example, suppose that one would like to make a purchase in market A, but has insufficient cash to do so. He then might sell short in market B to get cash to make the purchase in market A. See Noussair and Tucker (2003) for a discussion of this "liquidity" motive for trade in experimental asset markets.

[4] In the Ackert et al. experiment, the existence of a large monetary reward from accurate predictions and the fact that the same agents make predictions and trades mean that incentives exist to distort the price patterns in the market to try to win the prediction contest.

[5] In the King et al. study, the market has a capacity to short a number of units equal to 1.92 times the entire stock of units in existence. In the Ackert et al. study, roughly 2.2 times the total stock of units could be shorted, depending on the session. In our QL6 treatment, in which we observe prices below fundamentals, each agent has the ability to sell up to 6 units short, and the total number of units available is 18, so that 2.67 times the total stock of units could be shorted (one trader must keep a positive inventory, so it is not possible for all traders to have negative inventories).

relaxing the cash constraint by endowing each agent with additional cash might serve to increase prices in the same manner as Caginalp et al. (2000) observe in the absence of short selling. This possibility is our third hypothesis. Support for Hypothesis 3 would indicate that markets with short sales, even if they lead to lower overall price levels than in the absence of short sales, respond in a manner similar to changes in cash balances as markets in which no short sales are permitted.

HYPOTHESIS 3: In the presence of the ability to short sell, increasing the available cash balance in the market increases transaction prices.

II. Experimental Design

A. General Structure

The data for this study are gathered from 22 experimental sessions conducted at Emory University and at the University of Texas at Dallas. There are nine participants in each session. Subjects are undergraduate students recruited from economics classes at Emory and from classes and signs posted around campus at the University of Texas at Dallas. All of the subjects are inexperienced in asset market experiments. The sessions last approximately 1 hour and 45 minutes and subjects receive a participation fee of between 5 and 15 dollars, depending on the session, in addition to any earnings they received in the asset market.[6] Summary information about each session is given in Table I. For each session, indexed by identification number in the first column, the table indicates the treatment in effect, the location of the session, and any short-selling restrictions that are in effect.

In each session a market is constructed in which participants can trade an asset with a life of 15 periods. The parametric structure is identical to that of "design 4" described in Smith et al. (1988). At the end of each period, the asset pays a dividend that is independently drawn each period from a four-point distribution in which each unit of the asset pays a dividend of 0, 8, 28, and 60 tokens (experimental currency) with equal probability. A roll of a die after each period determines the dividend, which is common for all units and agents. Thus, the expected dividend in any period is equal to 24 tokens and the expected future dividend stream equals 24 tokens, multiplied by the number of time periods remaining. Since dividends are the only source of value for the asset, the fundamental value of the asset during any period t equals the expected future dividend stream $(24 * (16 - t))$.

Agents are endowed with units of the asset and a cash balance to begin the experiment. There are three types of agents and three agents of each type. Types differ only in their initial endowment of units of asset and cash. In 18 of the sessions (sessions 1–14 and 19–22), Type 1 has an initial endowment of

[6] Any losses incurred are deducted from the participation fee.

Table I

The Sessions

Eleven sessions are conducted at Emory University and 11 at the University of Texas at Dallas. There are eight different treatments, which differ in the short-sale restrictions in effect, the initial cash balances, and the number of markets. In the NSS treatment, no short selling is permitted. In the QL3 and QL6 treatments, any individual can hold a short position of up to three and six units, respectively, at any time. In the CR100 and CR150 treatments, agents can hold short positions, but they must have sufficient cash to cover 100% and 150% of the expected dividend payout on their short positions, respectively. In the FLX treatment, the cash reserve requirement is 100% of the short position if the last transaction price was above fundamental value, and 200% if it is below. In the treatments containing the prefix 10× (sessions 15–18), initial cash balances are 10 times greater than in the corresponding treatments. In the treatments with the suffix 2R, two 15-period markets operate sequentially.

Session	Treatment	Location	Restriction(s) in Effect
1	NSS	Emory	No short sales permitted
2	NSS	UTD	No short sales permitted
3–4	QL6	Emory	Net position ≥ -6
5	QL6	UTD	Net position ≥ -6
6	QL3	Emory	Net position ≥ -3
7	QL3	UTD	Net position ≥ -3
8–9	CR100	Emory	Cash balance $\geq 24 * (16 - t) *$ [net short position]
10	CR100	UTD	Cash balance $\geq 24 * (16 - t) *$ [net short position]
11	CR150	Emory	Cash balance $\geq 36 * (16 - t) *$ [net short position]
12	CR150	UTD	Cash balance $\geq 36 * (16 - t) *$ [net short position]
13	FLX	Emory	Cash balance $\geq 24 * (16 - t) *$ [net short position], if last transaction price $\geq 24 * (16 - t)$
			Cash balance $\geq 48 * (16 - t) *$ [net short position], if last transaction price $< 24 * (16 - t)$
14	FLX	UTD	Cash balance $\geq 24 * (16 - t) *$ [net short position], if last transaction price $\geq 24 * (16 - t)$
			Cash balance $\geq 48 * (16 - t) *$ [net short position], if last transaction price $< 24 * (16 - t)$
15	10×QL6	Emory	Net position ≥ -6
16	10×QL6	UTD	Net position ≥ -6
17	10×CR100	Emory	Cash balance $\geq 24 * (16 - t) *$ [net short position]
18	10×CR100	UTD	Cash balance $\geq 24 * (16 - t) *$ [net short position]
19	QL6-2R	Emory	Net position ≥ -6
20	QL6-2R	UTD	Net position ≥ -6
21	CR100-2R	Emory	Cash balance $\geq 24 * (16 - t) *$ [net short position]
22	CR100-2R	UTD	Cash balance $\geq 24 * (16 - t) *$ [net short position]

three units of asset and 255 tokens, Type 2 is endowed with two units of asset and 585 tokens, and Type 3 begins with one unit of asset and 945 tokens. Of these 18 sessions, the exchange rate in sessions 1–14 is one cent to one token. The exchange rates for sessions 19–22, which involve two repetitions and therefore twice as many periods, are one cent to two tokens. These initial cash and asset endowments are identical to those that Smith et al. (1988) use in their original study. In sessions 15–18, Types 1, 2, and 3 have initial cash endowments of 2,550, 5,850, and 9,450 tokens, respectively, and the same initial share endowments as in the other treatments. The exchange rate in these sessions is 1 cent to 10 tokens. The market is computerized and uses continuous double auction trading rules (Smith (1962)) implemented with the z-Tree computer program (Fischbacher (1999)) developed at the University of Zurich.

B. Timing of the Sessions

The sequence of events in sessions 1–18 is as follows. Upon arrival, subjects are trained in the mechanics of making purchases and sales with the z-Tree program. Training takes approximately 15 minutes. During the training phase, the experimenter reads from a script that consists of a step-by-step explanation of the interface and of how to make offers and trades. In the remainder of the training period (approximately 10 minutes), subjects practice buying and selling using the interface. Activity during the training phase does not count toward final earnings.

After the training phase is completed, the remainder of the instructions, which describe all other aspects of the experiment, is read aloud. Agents then receive their initial endowments of the asset and cash. The 15 periods of the asset market then proceed. Each period lasts 4 minutes. All subjects are free to purchase and sell units at any time provided that they do not violate the short-selling constraint in effect in the session. In addition, subjects are required to maintain a positive cash balance to make any purchases. If engaging in a trade would violate either the short sale or cash balance constraint, the computer program prohibits individuals from doing so. Each subject's cash and inventory of units carry over from one period to the next. A subject's earnings for the experiment are equal to his initial endowment of cash, plus his earnings from dividends, minus the dividends paid on his outstanding shares, plus the proceeds from his sale of shares, minus his expenditures on shares. Sessions 19–22 differ from those described above in that subjects participate in two full independent 15-period horizons.

C. Rules Limiting Short Sales

In all treatments, we place constraints on the ability of traders to take short positions. This allows us to test the hypotheses of interest in this paper. The constraints also prevent the possibility of bankruptcy, which occurs when an individual accumulates losses greater than the participation fee. In all cases, subjects are required to pay the dividends on any units that they have outstanding. Sessions 1 and 2 are replications of Smith et al. (1988) and in these sessions, short sales are not permitted. We refer to sessions 1 and 2 as the *No Short Selling* (NSS) treatment. Sessions 3–5 constitute the *Quantity Limit of Six Units* (QL6) treatment, and sessions 6 and 7 constitute the *Quantity Limit of Three Units* (QL3) treatment. In these sessions, a strict limit on the size of short positions is imposed. In the QL6 treatment, no subject can have a net short position of more than six units at any time. In the QL3 treatment, no subject can have a net short position of more than three units at any time.

In sessions 8–14, in which one of the Cash Reserve (CR) treatments is in effect, no absolute limit on the number of units outstanding is imposed, but each subject is required to maintain at least a minimum cash balance at all times. In sessions 8–10, in which the *Cash Reserve 100%* (CR100) treatment is in effect, the minimum cash balance is equal to the expected value of the future dividend stream of the short position held at the time. This is equal to $(24 * (16 - t) *$ [net short position]), where t denotes the current time period, and in which there remain $16 - t$ rounds of possible dividend payments. In the *Cash Reserve 150%* (CR150) treatment the minimum cash balance is equal to 150% of the expected value of the future dividend stream to be paid on short positions. The CR150 treatment is in effect in sessions 11 and 12. In sessions 13 and 14, the Flexible Cash (FLX) treatment is in effect. In this treatment, the cash reserve requirement is 100% of the future dividend stream $(24 * (16 - t) *$ [net short position]) when the last trading price is greater than the fundamental value and 200% of the future dividend stream when the last trade occurs at a price lower than the fundamental value. Thus, the short-selling constraint is tightened when prices fall below fundamentals.

In sessions 15–18, each type of agent is endowed with 10 times as much experimental currency as in the other sessions and short selling is permitted. In sessions 15 and 16, the 10×QL6 treatment is in effect. In this treatment, the same short-selling restriction is in effect as in the QL6 treatment. No agent can hold a net short position that exceeds six units at any time. In sessions 17 and 18, the 10×CR100 treatment is in effect, and the same restrictions on short positions as in the CR100 treatment apply. In sessions 19–22, which comprise the QL6-2R and CR100-2R treatments, and in which participants complete two 15-period horizons, the same short-sale constraints are in effect as in the QL6 and CR100 treatments.

III. Results

A. Evaluation of Hypotheses

The panels in Figures 1–3 illustrate the median transaction prices and volume in each period of sessions 1–18 of the experiment. Figure 1 contains the data from the NSS, QL3, and QL6 treatments, and illustrates the principal differences among the treatments. In Figure 1, the top panels indicate that bubbles occur in both sessions of the NSS treatment. The figures show that we have reproduced the price pattern documented in earlier studies. Although the bubble in session 2 is larger than in session 1, in session 1 the median prices are higher than fundamental values for nine consecutive periods and are more than double the fundamental value in periods 13 and 14. Our procedures therefore conform enough to those of previous studies to generate outcomes that are similar.

A comparison of the panels in the left portion of Figure 1 suggests that prices are lower in the QL3 treatment than under NSS and lower in QL6 than in QL3. In the QL3 and QL6 treatments, the median price exceeds fundamental

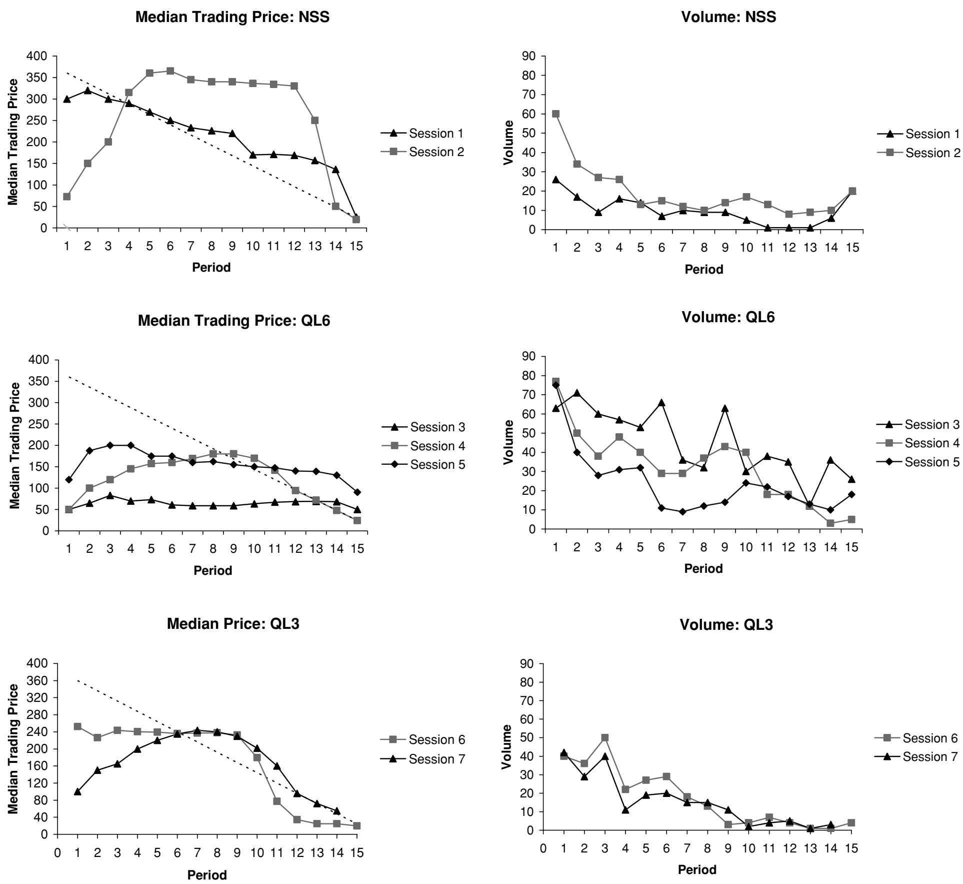

Figure 1. Time series of median transaction prices and volumes over time, NSS, QL3 and QL6 treatments, all sessions. In the panels on the left, the median transaction prices are shown for each of the 15 periods of each session for the NSS treatment, in which no short sales are allowed, and the QL3 and QL6 treatments, in which maximum short-sale positions of three and six units, respectively, are permitted. The dotted line indicates the fundamental value and each time series in each picture corresponds to one session. The panels on the right indicate the total transaction volume in each period of each session.

value on average in five and three periods, respectively. In contrast, under the NSS treatment, the average number of periods in which the median price exceeds fundamental value is 10.5 (in the sessions of the Smith et al. (1988) study with inexperienced subjects, the comparable measure is 11.42).[7] Figure 2 contains the per-period median price and quantity data for the CR100, CR150, and FLX treatments. The impression gained from Figures 1 and 2 is that CR150 generates lower prices than NSS and CR100 in turn generates lower prices than

[7] The data included in the calculations are from sessions 5, 7, 17, 10, 16, 18, and 26 of the Smith, Suchanek, and Williams (1988) study.

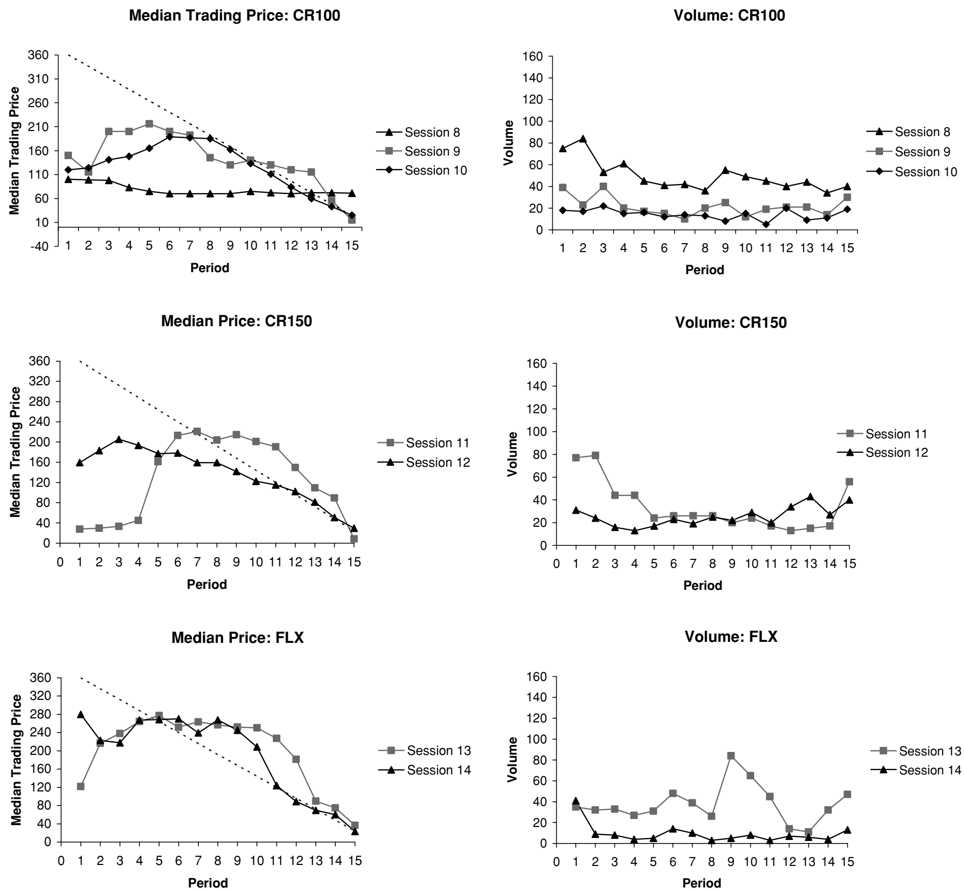

Figure 2. Time series of median transaction prices and volumes over time, CR100, CR150, and FLX treatments, all sessions. In the panels on the left, the median transaction prices are shown for each of the 15 periods of each session for the CR100, CR150, and FLX treatments. In the CR100 and CR150 treatments, individuals are required to hold cash balances equal to 100% and 150%, respectively, of the expected future dividend stream of their short positions. In the FLX treatment, the cash requirement is 100% of the expected future dividend stream of their short positions when the last transaction price is greater than or equal to the current fundamental value and 200% when it is less than the fundamental. The dotted line indicates the fundamental value and each time series in each picture corresponds to one session. The panels on the right indicate the total transaction volume in each period of each session. Each time series represents the data from one session.

CR150. The median price exceeds fundamental value on average for 2.3 periods in CR100 and for 4.5 periods in CR150. The figures also illustrate that the presence of short sales in conjunction with either a cash reserve requirement or a quantity limit does not induce prices to track fundamental values. The visual impression obtained from the figures is that the data reject Hypothesis 1 of Section I (prices track fundamental values under short selling), but support Hypothesis 2 (short selling reduces transaction prices).

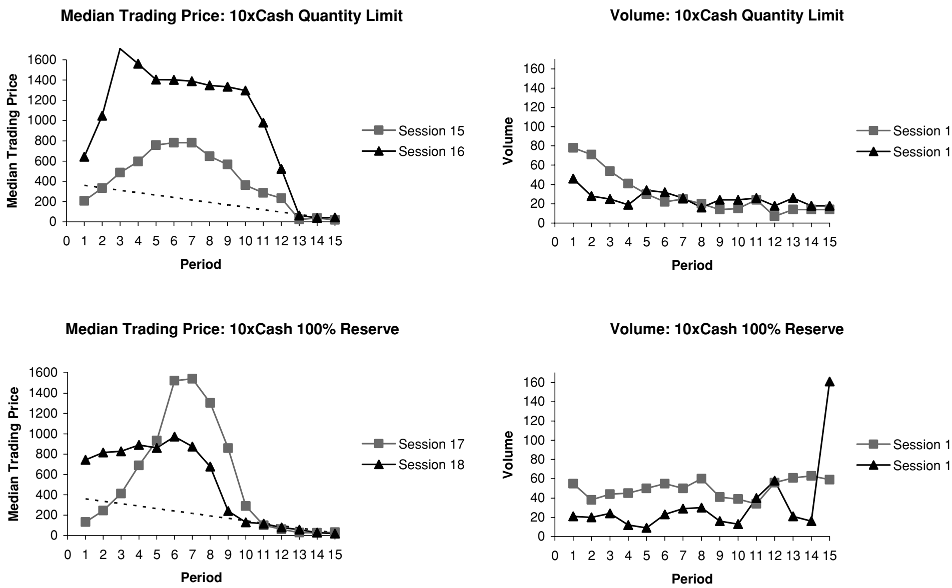

Figure 3. Time series of median transaction prices and volumes over time, 10×CR100 and 10×QL6 treatments, all sessions. In the panels on the left, the median transaction prices are shown for each of the 15 periods of each session for the 10×CR100 and the 10×QL6 treatments. In these two treatments each trader has an initial endowment of cash that is 10 times the amount of a corresponding trader in the other treatments. In the 10×CR100 treatment, individuals are required to hold cash balances equal to 100% of the expected future dividend stream of their short positions. In 10×QL6, the largest short position a trader could hold is six units. The dotted line indicates the fundamental value and each time series in each picture corresponds to one session. The panels on the right indicate the total transaction volume in each period of each session. Each time series represents the data from one session.

In supporting our results, we consider the effect of short selling on transaction prices at particular points in time over the life of the asset. The experimental design yields a natural measure of time, the market period. Thus, we use the average price over all transactions occurring in a given period as an observation on prices. We also use two measures of differences between median period prices and fundamental values over the entire life of the asset to support results 1 and 2. Tables II and III show, in the next-to-last column, the *Total Dispersion* of median prices from fundamentals in the seventh column of the table, where *Total Dispersion* is defined as the sum, over all 15 periods, of the absolute deviation of median period price from period fundamental value for the session indicated in the first column of the table. That is, $\textit{Total Dispersion} = \sum_t |\textit{MedianP}_t - f_t|$, where $\textit{MedianP}_t$ denotes the median transaction price in period t and f_t is the fundamental value in period t. A low *Total Dispersion* measure indicates a closer correspondence to fundamental values over the lifetime of the asset. A high *Total Dispersion* indicates large deviations of prices from fundamentals. The last measure given in the table is the *Average Bias*. This is the average, over

Table II

Observed Value of Bubble Measures, Sessions 1–18

This table reports the observed values of various measures of the magnitude of bubbles in each session, except for those with two rounds. $Amplitude = max_t\{(P_t - f_t)/f_t\} - min_t\{(P_t - f_t)/f_t\}$, where P_t and f_t equal the average transaction price and fundamental value in period t, respectively. $Normalized\ Deviation = \sum_t \sum_i |P_{it} - f_t|/(100 * TSU)$, where P_{it} is the price of the i^{th} transaction in period t, and TSU is the total stock of units that agents hold. $Turnover = (\Sigma_t q_t)/(TSU)$, where q_t is the quantity of units of the asset exchanged in period t. The boom and bust durations are the greatest number of consecutive periods that median transaction prices are above and below fundamental values, respectively. $Total\ Dispersion = \sum_t |MedianP_t - f_t|$, where $MedianP_t$ denotes the median transaction price in period t. $Average\ Bias = \sum_t (MedianP_t - f_t)/15$.

Session Number	Treatment	*Amplitude*	*Norm. Dev.*	*Turnover*	*Boom Duration*	*Bust Duration*	*Total Dispersion*	*Average Bias*
1	NSS (1)	1.98	3.46	8.39	12	3	533	23.8
2	NSS (2)	3.25	25.50	16	11	3	2,107	61.8
	Avg. NSS	2.61	14.48	12.20	11.5	3	1,320	42.8
3	QL6 (1)	1.89	60.72	37.67	2	13	2,008	−127.7
4	QL6 (2)	1.05	34.27	27.06	3	8	1,188	−71.2
5	QL6 (3)	3.53	22.40	19.78	6	9	1,134	−36.5
	Avg. QL6	2.17	39.13	28.17	3.7	10	1,443.33	−78.5
6	QL3 (1)	1.04	8.67	14.39	4	6	710.5	−25.7
7	QL3 (2)	0.97	13.31	12.06	5	6	967.5	−33.7
	Avg. QL3	1.00	10.99	13.23	4.5	6	839.0	−29.7
8	CR100 (1)	3.84	57.77	41.33	2	13	1,855	−114.2
9	CR100 (2)	1.25	13.60	18.11	4	10	925	−50.4
10	CR100 (3)	0.66	9.36	11.89	1	14	1,004.5	−66.8
	Avg. CR100	1.92	26.91	23.77	2.3	12.7	1,261.5	−77.1
11	CR150 (1)	1.79	48.70	28.22	8	7	1,716	−72.8
12	CR150 (2)	0.79	11.23	21.28	4	11	828	−53.8
	Avg. CR150	1.29	29.97	24.75	6	9	1,272	−63.3
13	FLX (1)	1.56	25.08	31.61	11	4	1,041.5	3.9
14	FLX (2)	0.80	4.40	7.78	7	5	574	1.1
	Avg. FLX	1.18	14.74	19.70	9	4.5	807.75	2.4
15	10×QL6 (1)	3.29	60.76	24.61	10	3	3,836.5	231.1
16	10×QL6 (2)	8.17	172.13	21.11	12	2	12,000	795.6
	Avg. 10×QL6	5.73	116.45	22.86	11	2.5	7,918.3	513.3
17	10×CR100 (1)	6.76	177.88	41.67	8	4	6,454	369.9
18	10×CR100 (2)	3.48	57.77	27.39	9	6	4,962	313.2
	Avg. 10×CR100	5.12	117.83	34.53	8.5	5	5,708	341.5

all 15 periods, of the deviation of median period price from period fundamental value. In other words, $Average\ Bias = \sum_t (MedianP_t - f_t)/15$. An *Average Bias* close to 0 indicates prices close to the fundamental values in an average sense. A negative (positive) *Average Bias* indicates a general tendency for prices to be below (above) fundamentals. The *Average Bias*, unlike the other measures, offsets positive and negative deviations from fundamental values. Thus, *Average Bias* is a measure of whether mean prices deviate from fundamentals, whereas *Total Dispersion* is a measure of variability. If both positive and negative bubbles occur in a session, *Average Bias* may be low, but *Total Dispersion* would

Table III

Observed Value of Bubble Measures, Twice-Repeated Treatments (Sessions 19–22)

This table reports similar statistics for the sessions that consist of two rounds. In this table, the terms *1st Market* and *2nd Market* refer to the first and second sequence of 15-period asset markets within a session.

Session Number	Treatment and Order of Market	*Amplitude*	*Norm. Dev.*	*Turnover*	*Boom Duration*	*Bust Duration*	*Total Dispersion*	*Average Bias*
19	QL6-2R (1) 1st Market	0.43	4.35	9.67	7	3	393	22.0
19	QL6-2R (1) 2nd Market	0.73	2.03	5.89	6	6	453	4.7
20	QL6-2R (2) 1st Market	0.80	3.19	8.06	11	4	500	−6.2
20	QL6-2R (2) 2nd Market	0.64	1.28	4.78	8	3	304	2.6
	Average (1st Market)	0.62	3.77	8.87	9	3.5	446.5	7.9
	Average (2nd Market)	0.69	1.66	5.34	7	4.5	378.5	3.6
21	CR100-2R(1) 1st Market	1.01	16.40	22.61	4	9	1,111.5	−23.3
21	CR100-2R(1) 2nd Market	1.49	20.67	24.83	4	9	1,299.0	−66.9
22	CR100-2R(2) 1st Market	0.53	6.40	11.5	3	7	558	−27.8
22	CR100-2R(2) 2nd Market	0.63	4.85	7.61	7	7	695.5	−33.7
	Average (1st Market)	0.77	11.40	17.06	3.5	8	834.7	−25.5
	Average (2nd Market)	1.06	12.76	16.22	5.5	8	997.2	−50.3

still be high. Hence, *Average Bias* and *Total Dispersion* together yield a clearer picture of bubble magnitude and direction than either measure separately.

Result 1: Under short selling, prices do not track fundamental values. Prices in the QL6, QL3, CR100, and CR150 treatments are all below fundamental values.

Support for Result 1: Table II shows that under all 10 sessions of the QL6, QL3, CR100, and CR150 treatments, the *Average Bias* is negative. This would be an extremely unlikely outcome if prices were equally likely to be above and below fundamental values. As is apparent from Figures 2 and 3, prices in these treatments tend to be below fundamentals for most of the time horizon.

Treating the difference between average price and fundamental value in each period of each session as the relevant unit of observation (which assumes that the difference between price and fundamental value is independent over periods and results in giving equal weight to all periods in all sessions) and evaluating the hypothesis that the average difference between average price and fundamental value equals 0 yields a t-statistic of 5.04 (d.f. = 44) in the QL6 treatment, with a p-value of less than 0.0001. In the QL3 treatment, the analogous t-statistic is 2.03 ($p = 0.0516$). In the CR100 and CR150 treatments, the corresponding t-statistics are 5.57 and 2.95, with p-values of less than 0.0001 and less than 0.01 for the two data sets, respectively.

The previous discussion shows that not only do prices in the short-selling treatments not track fundamental values, but rather they are systematically lower. Indeed, if sufficient short-selling capacity exists, prices are farther away from fundamental values than in the absence of short selling. The *Total Dispersion* averaged across the two sessions of the NSS treatment is 1,320, while in the QL6 treatment it is 1,443, indicating that when agents are permitted to short six units, prices are at least as far away from fundamentals as when they are not permitted to short sell. As we argue in Result 2, the more restrictive the constraint on short selling, the higher the price. Thus, our data support Hypothesis 2.

Result 2: The availability of short selling reduces transaction prices. The relaxation of constraints on short sales lowers prices. (a) Average prices in the QL6 treatment are lower than in the QL3 treatment, which are in turn lower than under the NSS treatment. (b) A cash reserve requirement of 100% of the expected future dividend stream leads to lower prices than the requirement of 150%, which in turn yields lower prices than under NSS.

Support for Result 2: Table II reveals that the *Average Bias* in each session of NSS (23.8 and 61.8) is greater than in any session of QL3 (−25.7 and −33.37), indicating higher prices in NSS than in QL3. In turn, the bias in each session of QL3 is greater than in any session of QL6 (−127.73, −71.20, and –36.57). The bias in each session of NSS is greater than in any session of CR150, where it is −72.8 and –53.87 in the two sessions. The average bias in CR150, −63.34, is greater than in CR100, −77.14. A t-test, in which the median prices averaged across all sessions in a treatment are compared between treatments, using each period as an observation (yielding 15 observations for each comparison between treatments), confirms that all of these differences are significant. The p-values for all pairwise comparisons between treatments are all below 0.001, except for the difference between CR150 versus CR100, where the test yields a p-value of 0.026.

Thus, we find that when sufficient short-selling capacity is available, prices are below fundamental values. Furthermore, the less stringent the constraints on short selling, the lower the prices. The absence of short-selling capacity is not at the origin of the bubble-and-crash pattern in laboratory asset markets. One reason that prices might be lower when short selling is present is that it increases the supply of shares available. If demand for shares is downward sloping,[8] the intersection between supply and demand will occur at a lower price

[8] Shleifer (1986) and Harris and Gurel (1986) argue that the demand for stocks is downward sloping.

if supply shifts outward, as can occur when short selling is instituted. Demand for shares in the experimental markets may be downward sloping (rather than horizontal at the fundamental value as rational expectations would postulate), if it is not exclusively determined by whether or not current prices are higher or lower than fundamentals. This might occur if some demand is speculative in nature, if demand is less than fully responsive to deviations from fundamentals, or if some agents make decision errors. If this were the case, the presence of more cash might shift demand outward and raise the equilibrium price, since it loosens the constraints on speculative purchases, as well as permits more scope for decision errors. Caginalp et al. (2000) observe that increasing the cash available for purchases increases prices in a setting in which short sales are not allowed. We find that this result carries over to our CR100 and QL6 treatments, supporting Hypothesis 3.

Result 3: Increasing the initial cash endowments to 10 times the level of the benchmark treatment increases asset prices.

Support for Result 3: Tables II–IV indicate the *Average Bias* and the *Total Dispersion* observed in the four sessions in which the cash endowment was 10 times the benchmark level. The biases in the two 10×CR100 sessions are 370 and 313, compared to –114, −50, and –67 in the CR100 treatment, which is identical to 10×CR100 except for initial cash endowments. Similarly, in the two 10×QL6 sessions, the bias is 231 and 796 compared to –128, −71, and –37 in the three QL6 sessions. The larger cash endowment also leads to larger departures from fundamental values. The *Total Dispersion* is greater in all four sessions in which the cash endowment is 10 times the baseline than in the six comparable CR100 and QL6 sessions.

Crashes occur later and bust durations are longer under 10×QL6 than under 10×CR100. The short-selling constraint becomes binding more quickly, at exactly six units, in the 10×QL6 sessions than in the 10×CR100 sessions, in which there is a large amount of cash available to cover the reserve requirement for larger short positions. The supply of shares can therefore respond more readily to high prices under 10×CR100, and in turn induce prices to fall.

Table IV

Observed Value of Bubble Measures, Comparable Previous Studies

This table reports the average values of the measures by session in previous studies.

	Amplitude	*Norm. Dev.*	*Turnover*	*Boom Duration*
Porter and Smith (1995)	1.53	N/A	5.49	10.15
Van Boening et al. (1993)	4.19	5.21	5.05	9.25
King et al. (1993), short selling, inexperienced participants only	1.61	11.88	6.67	9.50
Smith et al. (1988), inexperienced participants only	1.24	5.68	4.55	10.2
Smith, Van Boening, and Wellford (2000)	1.39	5.50	4.35	N/A

B. Exploratory Analysis

Despite the fact that prices are below fundamental values in the presence of short selling, the markets share many characteristics with those that exhibit price bubbles in the absence of short-selling capability. Tables II–IV illustrate the observed values of measures of the severity of price bubbles. Some of these measures are previously documented measures of bubble magnitudes in experimental markets that prior authors (King et al., (1993)) develop. Tables II and III report the values of the measures obtained in each session of our experiment and Table IV indicates the average values obtained in several previous studies in which the measures are reported. The data from the previous studies reported in the table include only markets in which subjects are inexperienced, to provide comparability with our data. No short sales are permitted in any of these previous studies.

The *Average Bias* and *Total Dispersion* measures reported in the table are described above. Again, *Total Dispersion* is defined as the sum, over all 15 periods, of the absolute deviation of median period price from period fundamental value, and *Average Bias* is the average, over all 15 periods, of the deviation of average period price from period fundamental value. The variable *Turnover* is a simple normalized measure of the amount of trading activity over the course of the 15 periods that the market is in operation, and is defined as $Turnover = (\Sigma_t q_t)/(TSU)$, where q_t is the quantity of units of the asset exchanged in period t and TSU is equal to the total stock of units (18 in our experiment). High turnover suggests the presence of an asset market bubble. If it were common knowledge that markets were to track fundamental values throughout the life of the asset, there would be little reason to exchange large quantities of units. Thus, large quantities suggest speculation on changes in future prices relative to fundamental values or possibly the presence of errors in decision making.

The *Amplitude* of a bubble is a measure of the magnitude of overall price changes relative to the fundamental value over the life of the asset. Specifically, $Amplitude = max_t\{(P_t - f_t)/f_t\} - min_t\{(P_t - f_t)/f_t\}$, where P_t and f_t equal the average transaction price and fundamental value in period t, respectively. In previous studies, high amplitudes are associated with the presence of price bubbles. Here, high amplitude indicates a lack of a tendency for prices to track fundamental values or to sell at a stable discount from the fundamental (which would be consistent with risk aversion on the part of traders).

The *Normalized (Absolute Price) Deviation* is a measure that takes both transaction prices and quantities exchanged into account. It is defined as $Normalized\ Deviation = \sum_t \sum_i |P_{it} - f_t|/(100 * TSU)$, where P_{it} is the price of the i^{th} transaction in period t. The statistic is divided by 100 to make it comparable to normalized deviations reported in previous studies, which are expressed in terms of 100 currency units. A high *Normalized Deviation* reflects high trading volumes and deviations of prices from fundamental values, indicating a market bubble. The *Boom Duration* is the maximum number of consecutive periods during the 15-period trading horizon that the median price exceeds the fundamental value. See King et al. (1993) for a discussion of *Turnover*, *Amplitude*, *Normalized Deviation*, and *Duration* as measures of the magnitude of bubbles. A related measure we consider here is the *Bust Duration*, which indicates the maximum number of consecutive periods that the median price is below the fundamental value. Result 4 below reveals that markets with short selling possess many of the properties of markets in which no short selling is permitted, namely high turnovers, amplitudes, and normalized deviations. The markets continue to exhibit the properties of bubble markets, with high trading volumes and endogenous price patterns that appear to have little connection to fundamental values.

Result 4: In the conditions with the least restrictive short-selling constraints (CR100 and QL6), the markets exhibit many of the properties associated with asset market bubbles: High transaction volume, large swings in prices relative to fundamental value, and sustained trading at prices that differ from fundamental values.

Support for Result 4: A comparison of the *Turnover*, *Amplitude*, and *Normalized Deviation* measures of bubbles yields similarly high, if not higher, values in the conditions with lax short-selling constraints,[9] CR100 and QL6, than under NSS and in previous studies in which short selling is not permitted. The *Amplitude* is similar in our three treatments, ranging from an average of 1.921 in CR100 to 2.617 in NSS, and *Turnover* remains remarkably high in the markets with short selling. Over 20 times the total stock of units trades over the course of a typical session. The *Normalized Deviations* in CR100 and QL6 are higher than those in the NSS condition.

The large price swings and high volumes observed in the markets with less restrictive short-selling constraints are further indication that prices are not induced to track fundamental values when short-selling capability is added.[10] Boom durations are obviously shorter in markets with short selling, reflecting the lower prices documented in Result 2. However, these short boom durations are more than made up for by long bust durations, or "pessimistic bubbles," which are sustained periods of time in which prices are lower than fundamental

[9] Lei et al. (2001) hypothesize that some of the volume of trade in this type of experimental asset market is due to the fact that agents have no alternative activity available in the experiment other than to trade in the asset market, and participants in the experiment tend to participate actively unless cautioned that it is not required to do so. They show that when another market is operating concurrently with the asset market, trade in the asset market decreases.

[10] This increase in turnover occurs partly because the supply to the market can increase if agents sell short. As an alternative measure of *Turnover*, we divide the transaction volume by the average number of positive shares held at the end of the trading period. In other words, we calculate $(\Sigma_t q_t)/(\Sigma_{it} max\{0, ISU_{it}\})$, where ISU_{it} is individual i's total holding of units of the asset at the conclusion of period t. This alternative measure includes in the denominator the number of shares that are actually in circulation rather than the sum of the net positive positions that traders hold. The average adjusted turnovers under this new measure are 16.23 for QL6 and 16.62 for CR100. Compared to the average NSS turnover of 12.20, we see that even accounting for the increased volume due to the greater capacity for transactions that short-selling creates, turnover is higher in the presence of sufficiently loose short-selling constraints.

values. Despite the significantly lower prices in markets with short selling, the markets fail to exhibit characteristics consistent with traders having common expectations that future prices will track fundamental values. Because of the low prices relative to fundamentals and the property that the fundamental value is decreasing over time, no market crashes are observed under short selling. The largest drop in median price from one period to the next at any time in the six sessions of CR100 and QL6 is 59.5, while in each of the two sessions of the NSS treatment there are drops of 105 in one session and 157 in the other.

The fact that less restrictive limits on short selling reduce prices suggests that a system in which the short-selling constraint is tightened when prices fall below fundamentals may have the effect of pushing prices closer to fundamentals. This possibility is explored in the FLX treatment, in which agents are required to hold an amount of cash equal to 200% of the expected dividend stream of their short position if the current price (as measured by the price at which the last transaction occurred) is below fundamental value, and 100% of the dividend stream if the current price is above fundamentals. The tightening of the short-sale constraint at prices below fundamentals is intended to attenuate the tendency for prices to fall below fundamentals. We recognize that the parameterization of the FLX treatment here, with the constraint tightening at prices equal to fundamentals, represents an idealized condition for the operation of the system. It supposes that the designer of the system is aware of the fundamental value. Since the change occurs exactly at fundamental values, it may also make the fundamental value more salient. As reported in Result 5, we find that prices in the FLX system are unbiased, although they do exhibit a bubble-and-crash pattern.

Result 5: The FLX system leads to the most unbiased prices of all of the systems studied here.

Support for Result 5: The biases in the two sessions of the Flexible Cash treatment are equal to 3.90 and 1.07, which are remarkably small compared to the biases observed in the NSS, QL3, QL6, CR100, and CR150 treatments. However, the *Amplitude* remains considerable in this treatment, illustrating that a bubble-and-crash pattern does persist. As shown in Figure 2, prices tend to exceed fundamental values during the middle periods of the life of the asset, and to be below fundamentals in the early and late periods.

The possibility of short selling serves to relax the constraint that agents cannot hold negative inventories. Table V shows the percentage of traders with binding cash and short-selling constraints in each of our treatments. The data in the table are the percentage of periods during which a trader's cash constraint is binding, averaged over all traders participating in a given treatment. Comparisons across treatments yield intuitive results. As short-selling constraints become more relaxed, they are binding on traders less frequently. Fewer traders hit their short-sale constraints in QL6 than in QL3, and fewer in QL3 than in NSS. The short-sale constraint is binding with roughly equal frequency in

Table V

Percentage of Periods in Which Short-Sale and Cash Constraints Are Binding, Averaged over All Traders

For each treatment the percentage of periods during which a subject's short-sale constraint is binding at the end of a period is calculated and averaged over periods and subjects. The percentage is shown in column 2. Column 3 displays the data from a similar calculation of the percentage of participants that have a binding cash constraint.

Treatment	% of Participants Who Hit Short-Sale Constraint, All Sessions (Averaged over Periods)	% of Participants Who Hit Cash Constraint, All Sessions (Averaged over Periods)
NSS	48.52	36.67
QL3	28.52	46.67
QL6	25.43	36.05
CR100	21.73	31.36
CR150	20.74	37.04
FLX	22.22	44.81
10×CR100	0	21.11
10×QL6	19.63	24.44

CR150 and CR100, but in both those treatments less frequently than in NSS. Adding more cash to initial endowments causes cash constraints to bind with lower frequency. In 10 × CR100 and 10 × QL6 traders hold zero cash balances less frequently than in CR100 and QL6.

Previous studies of experimental asset markets note that experience on the part of participants has a tendency to reduce asset market bubbles, and is associated with a closer correspondence between prices and fundamental values. The relevant experience in these studies consists of prior participation in an asset market for the full 15-period lifetime of the asset with the same other participants. In sessions 19–22, in which subjects trade over two consecutive 15-period horizons, under either the QL6 or CR100 short-selling constraints, we consider whether this effect appears under short selling. We denote the treatments in effect in these sessions as CR100-2R and QL6-2R.[11]

In these sessions, we also observe patterns analogous to those in previous studies. The measures of bubble magnitude are typically smaller during the second market in which individuals participate than in the first. However, here it is a downward price bias that is reduced with repetition rather than an upward bias. The data in Table III enable a comparison of the results from the first and second rounds of each of the four sessions. *Turnover* is on average lower in the second repetition, falling from 8.87 to 5.34 in the two repetitions of the QL6-2R treatment. In the CR100-2R treatment, average *Turnover* falls from 17.06 to 16.22 in the two repetitions, and the *Normalized Deviation* falls

[11] Each of these four sessions has two distinct consecutive 15-period trading horizons. The same group of nine subjects participated in both horizons. The duration of each period is 2.5 minutes in sessions 19–22 in comparison to 4 minutes per period in the other 18 sessions.

in three of the four sessions. The other measures of deviation from fundamental values, *Amplitude*, *Average Bias*, *Total Dispersion*, and *Bust Duration*, however, are less supportive of increasing convergence to fundamentals with more experience. This appears to be due to the absence of the strong and salient negative reinforcement from experiencing a market crash that occurs when short selling is not possible. When a crash occurs, subjects experience substantial and visible losses when their assets lose value rapidly with the crash. Under short selling, rapid crashes do not occur. This suggests that learning in asset market experiments is at least partially reinforcement driven.

IV. A Model of Feedback Behavior and Rational Speculation

In this section we report the results of a simulation model in which we reproduce some of the most prominent empirical patterns observed in our experimental data. This allows us to conjecture that experimental asset market bubbles are consistent with the interactive behavior of three types of agents. In our simulation model, participants in the market are assumed to use one of the three plausible trading strategies. The three trader types considered are proposed by DeLong et al. (1990, hereafter DSSW). The persistence of bubbles suggests the existence of agents who trade on momentum, purchasing units after price increases as if they expect prices to continue rising, and selling rapidly once a crash occurs. Following DSSW, we denote these traders as *feedback traders*. The existence of a crash suggests that there are also traders in the population who speculate, but realize that speculation on an upward price movement is unlikely to be profitable very late in the time horizon and thus sell their units at that time, thereby precipitating a crash. We call these traders *speculators*. We also include the third type DSSW propose, *passive investors*, who trade based on fundamental values, purchasing (selling) when prices are below (above) fundamentals.

The feedback traders make purchases and sales independent of fundamentals, and trade large quantities when market prices are changing rapidly. Feedback trading provides a plausible and precise structure for the "irrational" behavior in experimental asset markets that previous studies (e.g., Lei et al. (2001)) document. Such behavior consists of unprofitable purchases at very high prices during a market bubble, and the propensity to make unduly large numbers of transactions. Feedback trading generates both of these behaviors. Furthermore, the assumption that the expectations of feedback traders are adaptive is attractive because a growing body of experimental evidence suggests that expectations of the future are formed in an adaptive manner (see, e.g., Marimon and Sunder (1993), or Camera, Noussair, and Tucker (2003)).

DSSW show that the interaction of these three types of traders generates a bubble-and-crash pattern when they participate in a market in which an asset with a life of three periods is trading. We consider here an extension of the model. In particular, we postulate that agents using the same trading strategies as the three types in the DSSW model interact in markets with the parametric structure of our experimental markets. Each of the three trader types has a demand function that is linear in past, present, and/or future prices.

Feedback traders use only past prices, passive investors use only present prices, and speculators use only present and expected future prices in determining their respective strategies. A trader's demand may take on a negative value—in which case it becomes net supply to the market. The market clearing condition, that is, the requirement that quantity demanded equals quantity supplied, determines prices.

More specifically, the demand function of the feedback traders in period t is of the form $-\delta + \beta(p_{t-1} - p_{t-2})$, where p_{t-1} and p_{t-2} are the average transaction prices in periods $t-1$ and $t-2$, and δ and β are parameters to be estimated. Their trading is based on the current trend and they demand more, the more prices have been increasing. The demand function of passive investors is of the form $-\alpha(p_t - fv_t)$, a function of the difference between the current price and the current fundamental value. They purchase more at the lower prices that are related to fundamentals. Finally, the speculator, who has demand given by $\gamma(E(p_{t+1}) - p_t)$ trades based on the difference between the expected price in the next period and the current spot price, purchasing more, the greater the expected increase in prices. The values of the parameters are assumed to be identical in all treatments in order to study the effect of the restrictions on short sales, holding traders' rules of behavior constant (in effect assuming that types are exogenous).

The principal differences between our model and DSSW are the following. The first set of differences relates to the different environments. In DSSW, there are three periods, no cash or short-selling constraints, and infinitely many traders. Moreover, the speculator is better informed in that he has a better signal about the dividends than all other traders. In our environment, we have 15 periods, cash and short-selling constraints may be binding, and information on dividends is common to all types (although feedback traders make no use of dividend information).

The demand functions of the three types are very similar to DSSW with two important differences. The first major change relates to expected beliefs. Since the speculator must have beliefs on future prices, we require a model of such beliefs. Ideally, we would like the expectations of the speculators to reflect the true future prices. Unfortunately, since the number of traders is small, a single speculator's demand during this period may affect prices in the next period via the feedback traders, and hence the speculator's expectations in this period. This would destroy the uniqueness of the solution path and would add strategic considerations not intended for this model of a competitive environment. Therefore, we model the speculator as best responding to a population that contains both feedback and passive traders. We do this through two iterations. In the first iteration, we assume that the speculator believes that future prices will be at fundamental values. Given these beliefs and the demands of the other two types, prices are determined for each period. Then the speculator takes the new prices as his beliefs for each period and the system is solved again. This type of belief is known as a level-1 belief (Stahl (1993), Nagel (1995), Camerer, Ho, and Chong (2004)). In the last two periods (14 and 15) we fix the speculator's beliefs at fundamental values since the potential for speculation is minimal.

A second difference between our model and the DSSW model is in the modeling of the feedback trader. In the DSSW model, the feedback trader's demand intercept (the point at which prices do not change from period to period) is 0. In our model, with fewer traders and both cash and short-sale constraints, it is easy to get to a point such that one type of trader, the feedback trader, has all the shares and short-sale constraints prohibit other types from selling more shares. In this case, no more trading will occur, the price will not change, and the system will be "stuck." To avoid such a scenario, we assume a negative intercept $-\delta$ in the feedback trader's demand function. That is, if the price has been constant for the last two periods, the feedback trader will have a tendency to sell. Also, since calculation of the feedback trader's demand requires prices for the previous two periods, we set the first two periods' prices equal to the mean prices observed in our experiments in each of these two periods. This assumption is analogous to the benchmark period 0 in the DSSW model.

We first classify subjects in our experiment into one of the three trader types as follows: We classify a trader's behavior as passive in period t if the difference between the asset's fundamental value in period t and the average price in period t does not have the opposite sign from the change in the subject's holdings of the asset over the course of the period (the change in holdings is positive if his purchases exceed his sales for the period). Similarly, a subject is classified as a feedback trader in period t if the difference between the average price in periods $t-1$ and $t-2$ does not have the opposite sign as the change in the subject's holding in period t. We categorize the subject's behavior as consistent with that of a speculator in period t if the change in average price from period t to period $t+1$ does not have the opposite sign from the change in the subject's holding. Each subject receives a score with respect to each of the three types, with the score for each type increasing by 1 with every period in which the net change in his position is consistent with that type. At the end of period 15, we add up the scores for the individual and classify him as an agent of the type for which he has the highest score, provided that the score is greater than or equal to 8 (indicating that his behavior is consistent with that type for the majority of periods). If a subject has a score lower than 8 with respect to all three types, the subject is classified as "other," representing none of the three types. If a subject's score for two types is the same, and it equals at least 8 as well as exceeds the score for the other type, the individual is assigned 50% to each type. Similarly, a trader with an equal score of at least 8 for each of the three types is assigned a weight of 1/3 to each type. Table VI indicates the number of agents classified as each type in each session.

The table shows substantial consistency in the proportion of agents of each type by treatment. On average in each treatment, between 2.42 and 3.67 traders are classified as passive traders, between 1.67 and 2.92 are classified as speculators, and between 2.67 and 4.42 are categorized as feedback traders. Thus, there is evidence that the population of types is stable across treatments, which is consistent with the conjecture that a trader's type is exogenous.

We conduct two different types of simulations of the model to consider whether it captures the qualitative patterns in our data. The first set of

Table VI

Classification of Subjects into Types

Each subject receives a score with respect to each of the three types, with the score for each type equal to the number of periods in which subject's behavior is consistent with that type. A subject is classified as the type that receives the highest score, provided that the score is greater than 8, and as "other" otherwise. Ties are broken by assigning the corresponding fraction to each type. The number of subjects classified as each type is shown for each session, and the overall average across sessions is given in the bottom row.

Condition	Session	Passive	Speculator	Feedback	Other
NSS	1	3.83	3.83	1.33	0
	2	1	1.5	6.5	0
QL6	3	3	3	2	1
	4	2	1	4	2
	5	3.5	2.5	3	0
QL3	6	3	3.5	2.5	0
	7	1.5	1.5	6	0
CR100	8	2	4	3	0
	9	3	3	3	0
	10	6	2	1	0
CR150	11	2.83	0.83	3.33	2
	12	3.5	2.5	3	0
FLX	13	2.5	2.5	4	0
	14	3.33	0.83	4.83	0
10×QL6	15	3	2.5	2.5	1
	16	3.833333	0.333333	3.833333	1
10×CR100	17	2.3	3.83	1.83	1
	18	3.5	2	3.5	0
Proportions		0.331	0.254	0.365	0.049

simulations has six free parameters, namely, four demand parameters, δ, β, α, and γ, and two parameters for the proportion of the trader types, *Speculators Prop* and *Passive Prop*. The third proportion, *Feedback Prop.*, is equal to one minus the other two proportions. We use the amoeba minimization algorithm to find the parameter values that minimize the root mean squared deviation between our average simulated prices and the average observed prices in our experiments in each period. The second set of simulations restricts the parameters *Speculators Prop* and *Passive Prop* to be the overall average proportions obtained from the classification reported in Table VI. The proportion classified as "other" is randomly assigned to the three behavioral types with probabilities equal to their proportions in the population. The second set of simulations estimates the proportion parameters along with the four demand parameters.

Each set of simulations includes 150 repetitions, or 150 groups of nine simulated traders. The proportion of each type of trader in each group varies. In the first set of simulations, each trader in each group of nine traders draws his type at random with probabilities according to *Speculators Prop*, *Passive Prop*, and *Feedback Prop.* Each trader begins period 1 with the initial endowments of money and shares that existed in the experiment. Next, there is a grid search on prices in each period. Prices are determined by setting net demand equal

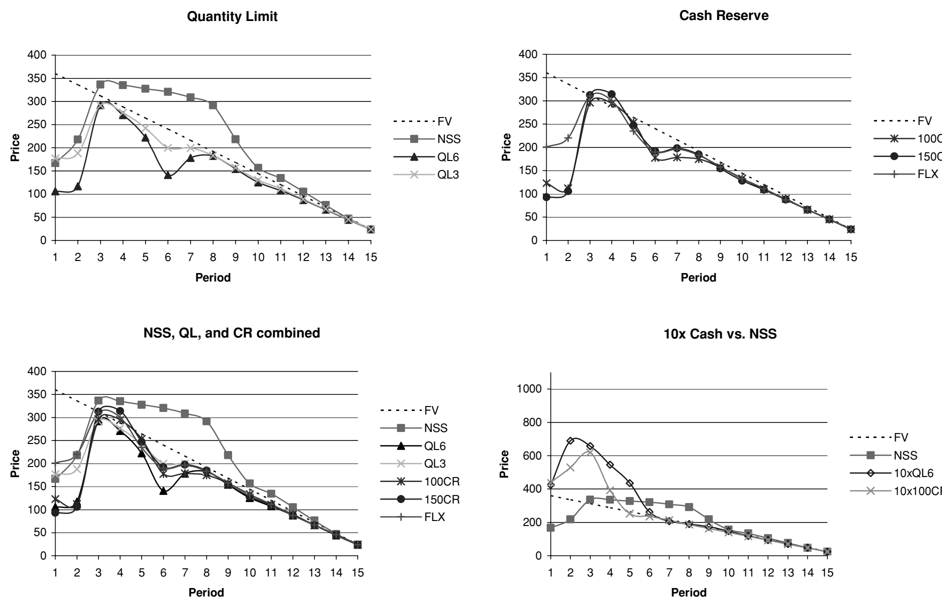

Figure 4. Aggregate price patterns resulting from simulation model for different treatments of the experiment, all parameters free. The graphs show price patterns in simulations based on the trader types proposed by DeLong et al. (1990), with proportions of trader types and demand parameters estimated on the pooled experimental data by minimizing the distance between simulated and actual prices for all treatments. The figures show the price patterns, averaged across 150 simulated markets of nine traders each. Traders in each simulated market are sampled from a population containing the estimated proportions of types and behave according to the demand functions assigned to their type with the corresponding parameter estimates.

to 0, that is, equating demand and supply. When net demand is positive, the price is increased, and when it is negative, the price is decreased. The price is adjusted until the net excess demand equals 0. We solve for period prices one by one, proceeding sequentially. There are two iterations through the 15 periods to solve for prices. The first iteration determines the beliefs of the speculators; the second iteration solves for the actual prices.

The aggregate price patterns resulting from the first set of simulations are graphed in Figure 4, and those from the second set of simulations are shown in Figure 5. The parameter estimates for the two simulations are given in Table VII. The variables *Speculators Prop* and *Passive Prop* are the estimated proportions of speculators (20%) and passive traders (37%) in the population. The remaining 43% are feedback traders. These estimates are close to those obtained from the classification from the actual experimental data in Table VI, indicating that the estimated parameters are close to the true parameters and that the classification system is reasonable. The demand parameters are very close for each of the types between the two sets of simulations.

Both sets of simulations replicate many of the prominent patterns we observe in our experiment, including the major differences in outcomes between

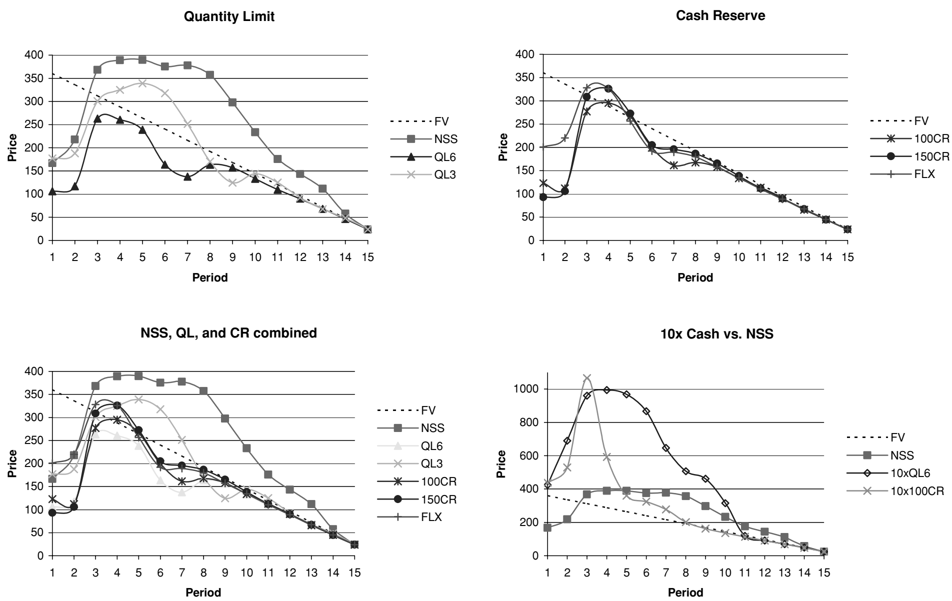

Figure 5. Aggregate price patterns resulting from simulation model for different treatments of the experiment, proportions of types restricted to actual proportions. The graphs show price patterns in simulations based on the trader types proposed by DeLong et al. (1990), with proportions of traders based on the proportions of experimental subjects classified as each type by a scoring method. Demand parameters are estimated on the pooled experimental data by minimizing the distance between simulated and actual prices. The figures show the price patterns, averaged across 150 simulated markets of nine traders each. Traders in each simulated market are sampled from a population containing the actual proportions of types in the experiments and behave according to the demand functions assigned to their type with the corresponding parameter estimates.

treatments: (1) The benchmark treatment NSS displays the largest positive price bubble in both magnitude and duration relative to all treatments that have the same cash constraint but more lax short-selling constraints. (2) All treatments display an early increase in prices, followed by a decrease. (3) The rise and fall in prices does not imply a bubble. In the sessions with the lax short-selling restrictions, prices remain below fundamental values for the majority of the asset's life. (4) The ranking of prices in the simulation is the same as in our sessions: NSS $>$ QL3 $>$ QL6 and NSS $>$ CR150 $>$ CR100. (5) The FLX treatment generates prices closest to fundamental values. (6) The two treatments with higher cash balances, 10 $\times$ CR100 and 10 $\times$ QL6, display bubbles far larger in magnitude than in the other treatments. (7) The 10 $\times$ CR100 condition has shorter bubble duration than 10 $\times$ QL6.[12]

[12] In the 10 $\times$ QL6 treatments, supply is not as responsive to demand from feedback traders and speculators. The short-selling limit is binding earlier in 10 $\times$ QL6 than under 10 $\times$ CR100, because cash is abundant in 10 $\times$ CR100, making it usually feasible to hold a short position of more than six units.

Table VII

Parameter Estimates for the Model of Feedback Traders, Passive Investors, and Speculators for the Experimental Data

The demand parameters α, β, γ, and δ, as well as the proportion of traders of the speculator and feedback types are estimated by minimizing the distance between actual and simulated prices, in all treatments. The demand function of feedback traders in period t is of the form $-\delta + \beta(p_{t-1} - p_{t-2})$, where p_{t-1} and p_{t-2} are the average transaction prices in periods $t-1$ and $t-2$. The demand function of the passive investors in period t is of the form $-\alpha(p_t - fv_t)$, where fv_t is the fundamental value in period t. The demand function of the speculators in period t is of the form $\gamma(E(p_{t+1}) - p_t)$, a function of the difference between the expected price in the next period and the current spot price. The second column contains the joint estimates of the six parameters. The third column contains the estimates of α, β, γ, δ when the proportions of trader types are constrained to be the actual percentages in the experiment, shown in Table VI and the demand parameters are estimated by minimizing the distance between actual and simulated prices in all treatments.

Parameter	Estimate (All Parameters Free)	Estimate (Proportion Parameters Fixed)
α (passive investor demand parameter)	0.699	0.749
β (feedback trader demand parameter)	0.120	0.129
γ (speculator demand parameter)	0.510	0.552
δ (feedback trader intercept)	0.471	0.476
Speculators Prop	0.201	0.254
Passive Prop	0.366	0.331

Table VIII shows the bubble measures for the second set of simulations. We see that these patterns are similar to those shown in Tables II–IV. Specifically, the lax short-selling conditions do not eliminate the average bias but rather make it negative. And although they have somewhat lower *Amplitude*

Table VIII

Observed Value of Bubble Measures, Simulations

This table contains the average values of various bubble measures from the simulations. $Amplitude = max_t\{(P_t - f_t)/f_t\} - min_t\{(P_t - f_t)/f_t\}$, where P_t and f_t equal the average transaction price and fundamental value in period t, respectively. $Norm.\ Dev. = \sum_t \sum_i |P_{it} - f_t|/(100 * TSU)$, where P_{it} is the price of the i^{th} transaction in period t, and TSU is the total stock of units agents hold. $Turnover = (\Sigma_t q_t)/(TSU)$, where q_t is the quantity of units of the asset exchanged in period t. The boom and bust durations are the greatest number of consecutive periods that median transaction prices are above and below fundamental values within a session, respectively. $Total\ Dispersion = \sum_t |MedianP_t - f_t|$, where $MedianP_t$ denotes the median transaction price in period t. $Average\ Bias = \sum_t (MedianP_t - f_t)/15$.

Condition	*Amplitude*	*Norm. Dev.*	*Turnover*	*Boom Duration*	*Bust Duration*	*Total Dispersion*	*Avg. Bias*
NSS	0.85	0.292	1.36	6.98	2.41	592.59	41.55
QL3	0.30	1.306	6.22	1.29	6.05	221.14	−14.09
QL6	0.49	2.400	5.04	1.02	6.19	311.14	−23.93
100CR	0.40	1.184	4.29	1.05	6.65	229.05	−15.80
150CR	0.48	0.999	3.90	1.83	5.67	270.25	−9.94
FLX	0.37	0.859	3.58	1.40	6.06	242.75	−11.82
10×QL6	1.52	7.395	6.63	10.63	2.47	902.31	65.84
10×100CR	1.10	4.596	5.90	5.59	5.61	500.66	30.84

Table IX

Profits by Type in the Simulations

This table indicates the average profits that traders of each type earned in the simulation. The percentage is calculated separately for each treatment. The last row contains the average across all treatments.

Condition	Feedback	Passive	Speculator
NSS	588.462	804.578	809.963
QL3	338.063	991.386	875.593
QL6	−339.259	1,310.04	1,489.27
CR100	245.527	1,187.28	760.129
CR150	348.135	1,090.48	787.137
FLX	408.29	1,026.62	773.535
10×CR100	−1,520.65	2,301.73	1,734.58
10×QL6	−2,532.99	3,606.7	2,237.24
Average	−308.053	1,539.852	1,183.431

relative to the NSS condition, they increase *Turnover* and therefore *Normalized Deviation*.[13] Relaxing the short-selling constraint from a quantity limit of three to six increases all measures of deviation from fundamentals (other than boom duration). Increasing the amount of cash in the system also increases all measures of deviation from fundamentals (other than bust duration).

The three types vary in their assumptions on rationality and expectation formation. Thus, the three types of traders in the simulations differ from each other in the profits they generate, and the difference varies across treatments. We examine whether similar profit levels are observed in the experimental data as in the simulations (with the same proportion of types). Consistency between these two measures would suggest that the correspondence of aggregate price patterns between the experiment and the simulations reflects consistency of individual-level behavior.

Tables IX and X show average profits by type in the simulations and the experiment. The data in the table are the final profits of individuals minus the expected payoff of the initial cash and asset position of the trader. As might be expected, the experimental sessions exhibit more variance than the simulations. In the simulations, the passive traders earn the highest profits, followed by the speculators and the feedback traders.[14] The feedback trader, whose strategy is not necessarily rational, is the only type that loses money on average in

[13] In the simulations, each trader is either a buyer or a seller in a period. In the experiments, a trader can be both a buyer and seller by repeatedly buying and selling within a period. Hence, the observed trading volumes in the experiment are far higher than in the simulations. Nevertheless, the ranking of trading volumes in the experimental conditions is preserved in the simulations. Specifically, relaxing short-selling constraints appears to increase trading volumes.

[14] The speculator is not able to earn more profit than a passive trader even through he is able to accurately predict future prices. This is because predicting prices correctly does not necessarily mean that one can find demand or supply at the current prices when the speculator wishes to buy or sell. As such, the speculator may be stuck with excess stock as the crash occurs or with not enough stock while a bubble is in a boom phase.

Table X
Profits by Type in the Experiments

This table indicates the average profits that traders of each type earned in the experiment. The percentage is calculated separately for each treatment.

Condition	Feedback	Passive	Speculator
NSS	477.3	−313.0	813.0
QL3	158.0	2,818.3	1,312.0
QL6	2,542.2	2,486.8	−355.8
CR100	−98.8	2,202.8	594.6
CR150	1,147.3	1,378.2	92.3
FLX	516.5	−668.8	2,069.6
10×CR100	−3,855.0	7,713.2	−556.5
10×QL6	−2,091.4	3,228.2	10,139.0
Average	−150.5	2,355.7	1,763.5

any treatments in the simulations. The feedback trader performs worse in treatments with looser cash and short-selling constraints, as the tighter constraints restrict his ability to adopt costly strategies. The passive trader earns the most in the treatments in which prices deviate the most from fundamental values, as he is the most active in those situations, and he makes profits on the difference between price and fundamental value. Both the passive trader and the speculator tend to have greater earnings when the feedback trader has lower earnings, as both types take advantage of the irrational behavior of the feedback trader. The last effect induces a positive correlation in the earnings of the passive and speculator types. The looser the cash and short-selling constraints, the higher are the earnings of the speculator.

In the experimental data, many of the above patterns also appear, at least to some extent. The feedback trader performs fairly well in treatments with tight short-sale restrictions (NSS, QL3, CR150, FLX). In these sessions, the cash and short-selling constraints protect feedback traders from making too many mistakes. In contrast, in the treatments CR100, 10 × CR100, and 10 × QL6, when either restriction (cash or short selling) is lax, the feedback trader performs poorly and tends to lose money relative to the expected earnings of the initial position. An exception to this rule is QL6, in which constraints are loose and the feedback type earns high profits in the experiment. This may be because in two of the sessions prices are below fundamentals but exhibit a slight but sustained upward trend, so that agents who accumulate holdings at these favorable prices may be classified as feedback traders. In the 10× treatments, in which very large bubbles are observed, the feedback trader performs the poorest, as he is unable to liquidate at favorable prices the large holdings accumulated in the boom phase of the market. As in the simulations, the passive trader earns the highest profit of the three types and does especially well when prices deviate the most from fundamental values. The passive trader does relatively poorly in the treatments with the tightest constraints (NSS and FLX), presumably due to limits on the ability to take advantage of the feedback trader that the constraints impose. Overall, the patterns that profits exhibit across types and treatments are consistent between experiment and simulations, indicating that individual-level features of the experimental data are captured in the simulations.

Although the incidence and magnitude of bubbles varies across treatments, the only environmental differences between treatments are the nature of the cash and short-selling constraints. This suggests that the constraints influence price patterns by disproportionately affecting different trader types and thereby changing their relative influence on market activity. For example, because the feedback trader is the "irrational" type, it may be the case that the treatments that reduce bubbles do so because they cause feedback traders' constraints to bind, in effect reducing their influence on market activity. Similarly, a treatment that relaxes the constraints on passive traders and speculators may induce prices to correspond more closely to fundamental values because it would reduce the share of activity attributable to feedback traders.

We first explore how the constraints bind on each trader type in each treatment. We then consider the issue of how the distribution of trader types influences price patterns and how these effects might vary depending on the treatment. Tables XI and XII indicate the average number of periods, out of a total of 15, that each of the two constraints (cash and short-sale) binds per agent in each treatment. Table XI displays a subject's frequency of hitting each of his constraints by classification into trader type. Table XII shows the corresponding figures for the simulations. The left side of each table indicates the extent to which cash constraints bind for each type in each treatment. The right side shows the average frequency of binding short-sale constraints.

As might be expected, the experiment displays higher variance than the simulations. In the simulations, the cash constraint is least likely to bind for both the passive and the feedback traders in the 10× treatments. Speculators hit

Table XI

Average Number of Periods Simulated Traders' Constraints Are Binding, by Trader Type

This table shows, for each treatment and each trader type, the number of periods during which a subject's demand (supply) cannot be met due to the cash (short-selling) constraint, averaged across subjects and over simulations.

Cash Constraint Binding				Short-Selling Constraint Binding			
Condition	Feedback	Passive	Speculator	Condition	Feedback	Passive	Speculator
NSS	3.371	1.099	0.221	NSS	6.868	1.557	7.480
QL3	1.157	4.587	0.081	QL3	6.614	0.026	4.077
QL6	2.208	5.188	0.109	QL6	5.820	0.000	2.800
CR100	1.611	4.841	0.052	CR100	5.881	0.127	3.161
CR150	1.450	4.627	0.036	CR150	6.343	0.130	2.717
FLX	1.340	4.762	0.032	FLX	6.736	0.074	2.576
10×CR100	0.769	1.845	0.024	10×CR100	4.656	0.360	4.493
10×QL6	1.409	0.092	0.151	10×QL6	8.575	1.337	9.215

Table XII

Average Number of Periods Subjects' Constraints Are Binding, by Trader Type

This table shows, for each treatment and each trader type, the number periods during which a subject's cash (short-sale) constraint restricts that subject's demand (supply) at any time during the period. Specifically, if at some point during the period, the last observed trading price of the asset is such that the cash balance and inventory of shares of the subject do not enable the subject to buy or sell at that price, we say that a constraint is binding in that period. This number is averaged across subjects classified as each trader type and across sessions.

Cash Constraint Binding				Short-Selling Constraint Binding			
Condition	Feedback	Passive	Speculator	Condition	Feedback	Passive	Speculator
NSS	4.335	3.000	1.995	NSS	2.667	3.000	7.000
QL3	1.500	1.000	2.500	QL3	3.495	0.000	1.001
QL6	3.795	2.500	1.200	QL6	0.000	0.251	4.200
CR100	0.250	0.250	1.000	CR100	3.495	0.000	3.270
CR150	0.195	8.505	4.005	CR150	1.200	0.000	3.105
FLX	4.665	3.000	3.195	FLX	1.005	6.000	1.605
10×CR100	1.800	0.195	1.995	10×CR100	4.005	0.000	1.250
10×QL6	3.795	2.505	1.200	10×QL6	0.000	0.255	4.200

their cash constraints least frequently in treatments in which the price falls in most periods because they sell in anticipation of the price declines. The highest incidence of binding cash constraints for speculators exists in the 10×QL6 and the NSS treatments, in which the price rises for much of the sessions, and in the QL6, treatment, where it remains fairly constant over time for most of the sessions. Because passive traders make larger net purchases the farther prices are below fundamentals, their cash constraints bind most often in the treatments in which prices tend to linger below fundamental values, especially when the short-selling constraints take the form of quantity limits rather than cash reserve requirements, and least often in treatments in which prices tend to exceed the fundamental value. Feedback traders' cash constraints bind most frequently in treatments in which there are prolonged price increases.

The right side of Table XI indicates the frequency with which the short-selling constraints bind. The greatest impact of the short-selling constraint appears to be on the speculators. That is, relaxing short selling drastically reduces the incidence of speculators in the simulation and the experiments who hit their short-selling constraint. From the simulation it appears that relaxing short-selling constraints has the least effect on feedback traders, whose constraints bind with roughly the same frequency even when they are lax. This means that in situations in which they would sell to capacity under a tight short-sale restriction, they typically respond to an increase in short-selling capacity by selling up to the new capacity. Feedback traders thus sell more units when short-selling constraints are loosened, pushing prices downward.

The behavior of passive traders tends to push prices back toward fundamentals, but they do not have the capacity to move the market price sufficiently to do so, as their cash constraints bind much more often when short selling is permitted. Cash restrictions prevent them from restoring prices to fundamental values and prices remain too low. Because short selling reduces the magnitudes of booms and crashes, speculators reduce their activity and thus also fail to push prices toward fundamentals.

In the simulations, the short-selling constraints are more likely to be binding for all three types than are the cash constraints. The fact that the short-selling constraint is often binding for feedback traders and speculators in the NSS treatment supports the result that the absence of short-selling ability is at least in part responsible for prices being higher than fundamentals in the Smith et al. (1988) experimental design. Passive traders, as might be expected, are more likely to hit their short-selling constraints in the treatments in which prices exceed fundamental values for most of the asset's life, namely, NSS, $10 \times$ CR100, and $10 \times$ QL6. Speculators hit their short-selling constraint more often when there are large bubbles because they take large short positions in anticipation of future crashes. Feedback traders hit their short-selling constraints frequently in all treatments because of the general trend of declining overall prices as the fundamental value declines in all treatments. This occurs most frequently in the $10 \times$ treatments, in which prices exhibit the largest crashes.

In Table XII, which corresponds to the experimental data, some of the patterns evident in the simulations are less evident due to the high variability. However, we observe several patterns similar to the simulations. Specifically, the feedback type is more cash constrained in the conditions characterized by sustained bubbles, particularly NSS and $10 \times$ QL6, than in most of the other conditions. Unlike the simulations, the subjects identified as speculators in the experiment do not display the same degree of short-selling activity in the $10 \times$ treatments. However, as in the simulations, the speculators engage in substantially more short selling than the other two types in most conditions and are most likely to hit the short-sale constraint in the NSS and the $10 \times$ QL6 condition. As in the simulations, the passive types are much less likely to hit short-selling constraints than the other two types. The feedback traders hit their short-selling constraints in the experiment much less than in the simulations but in both settings there is no clear relationship between the restrictiveness of the short-selling constraint and likelihood that the constraint is binding on individuals.

The distribution of types in the population also presumably affects the incidence and magnitude of bubbles. Because changing the constraints affects agents of different types in a different manner, the distribution of types might affect the market differently depending on the cash and short-sale constraints in effect. Similarly, the efficacy of the constraints may depend on the proportions of traders of each type. The effect of this distribution is considered in Figure 6, which shows price patterns that result from varying the proportion of agents of each type from 0 to 1 in the simulations, keeping the proportions of each of the other two types equal to half of the remaining population. As the figure shows, the treatments NSS, $10 \times$ CR100, and $10 \times$ QL6 exhibit a rather similar pattern to each other, while the other five treatments exhibit a similar pattern to each

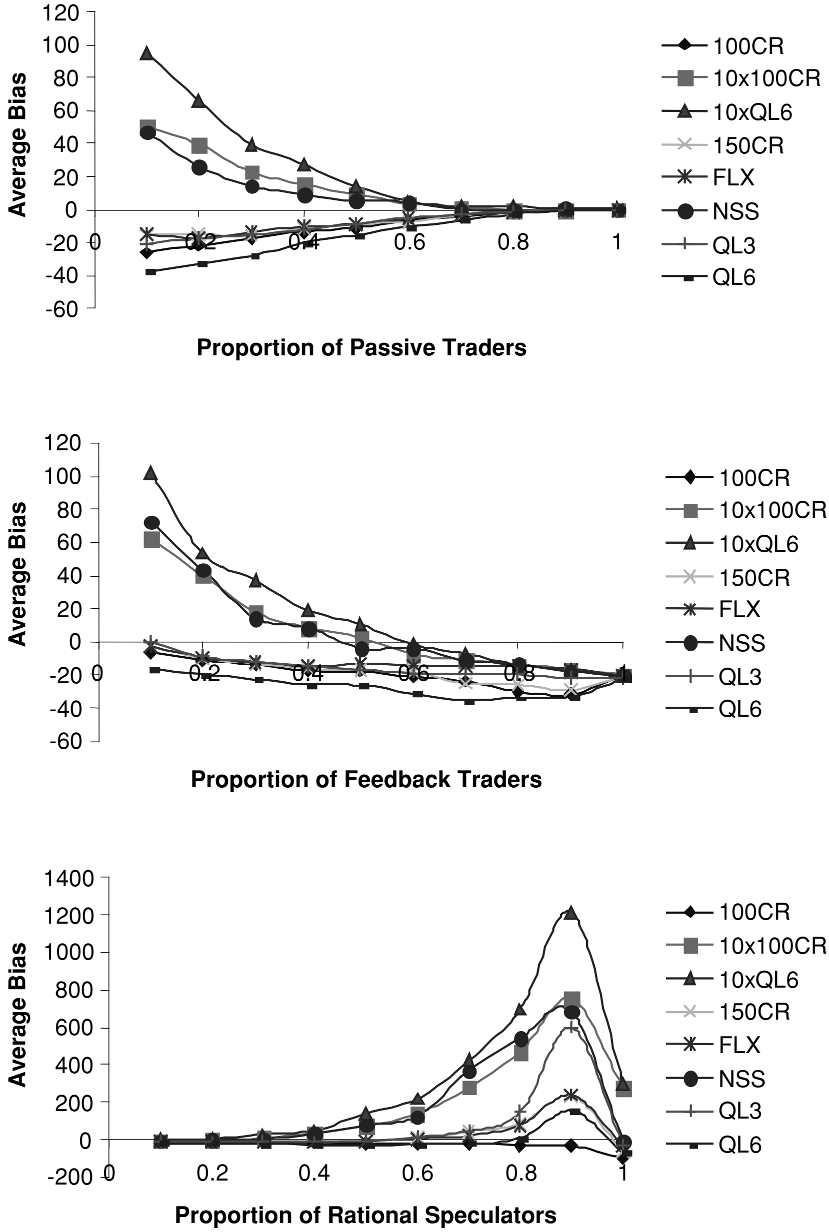

Figure 6. Average bias under different proportions of each type. The figure above shows the average bias generated in a simulation in which the number of traders of each of the three types varies. The first part of the figure indicates, for each treatment, the *Average Bias*, where *Average Bias* $= \sum_t (MedianP_t - f_t)/15$, in simulated markets in which the proportion of passive traders, Prop(passive), is indicated on the horizontal axis. The proportions of each of the other two types, speculator and feedback, are equal to (1 – Prop(passive)/2). The second and third parts of the figure indicate the average bias as a function of the fraction of feedback traders and speculators in the market (and assuming that an equal proportion of the remaining traders is of each of the two other types).

other. Increasing the proportion of feedback traders has the effect of reducing prices. While it appears to have the effect of mitigating positive bubbles, the lower average bias is actually due to exacerbating crashes. Increasing the proportion of passive traders has the effect of moving prices closer to fundamental values. Increasing the proportion of speculators raises prices unless speculators comprise almost the entire population. A high population of speculators leads to very large bubbles in the NSS treatment especially when some feedback traders are present. That is, in our simulations, positive bubbles owe their existence to a combination of speculators and feedback traders. This pattern is consistent with the observations of Lei et al. (2001), who establish that bubbles in experimental asset markets are a result of both speculation and errors in decision making. Speculation is captured in the behavior of our speculators. Errors in decision making that Lei et al. identify, which consist of purchases at prices higher than the maximum possible realization of the future dividend stream, are highly consistent with the behavior of feedback traders because the purchase errors in Lei et al.'s analysis almost always occur immediately after a run-up in prices.

The effectiveness of different constraints on trading depends on characteristics of the population of traders. When a high proportion consists of speculators, loosening short-selling constraints moves prices closer to fundamentals, while increasing cash balances exacerbates the bubble phenomenon. Increasing the percentage of feedback traders improves price efficiency in high cash and the NSS treatments, as long as the percentage is not too high. Under short selling, the greater the percentage of feedback traders in the market, the farther below fundamentals are prices. A sufficiently high proportion of feedback traders generates prices below fundamentals in all treatments. Increasing the proportion of passive traders moves prices closer to fundamentals independently of the constraints in effect, but the marginal gain is greatest when the proportion of passive traders is low and when the treatment is one in which the largest deviations from fundamentals occur.

V. Conclusion

We examine the effect of the availability of short selling in asset markets with a structure that is known to generate a bubble-and-crash pattern in the absence of short-sale capacity. Our data show that short selling has the effect of reducing market prices. Prices in our markets with relatively loose short-selling constraints exceed the fundamental value only occasionally, for brief intervals, and by relatively small magnitudes. However, we find that allowing a sufficiently large short-selling capacity reduces prices to levels below fundamental values. Thus, although we identify an institution that appears to prevent prices from exceeding fundamental values in experimental asset markets, short selling does not solve the problem of market prices failing to reflect fundamental values. The conclusion of Ackert et al. (2001), that short selling induces unbiased asset pricing, appears to be specific to a particular range of parameters on the short-selling constraints.

Our findings suggest that rather than inducing rational expectations, short selling merely influences the supply of and demand for the asset, which is in part determined by forces other than the relationship between current prices and fundamental values. Comparisons of market behavior between the different treatments in our study reinforce this view. As short-sale restrictions are relaxed, releasing additional potential supply of the asset, prices fall. As the available cash in the system is increased, relaxing the constraint on the quantities that individuals may purchase, prices rise. The positive correlation between cash balances and the magnitude of price bubbles is documented in previous research (Caginalp et al. (2000)),[15] and in this study we establish that this correlation extends to markets with short selling.

The simulations in Section IV allow us to advance what we believe to be a plausible conjecture about the structure and origins of this demand and supply for the asset. We show that a market populated with speculators, feedback traders, and passive traders can generate empirical patterns similar to those we observe. The existence of speculators is consistent with the hypothesis of a lack of common knowledge of rationality on the part of market participants (Smith (1994)). The presence of feedback traders is a more structured formulation of the claim that errors in decision-making occur during bubble formation (Lei et al. (2001), Noussair and Plott (2006)). Feedback trading is consistent with myopia (Gneezy and Potters (1997), Gneezy, Kapteyn, and Potters (2003)), miscalculation of expected utility (McKelvey and Palfrey (1995)), and reinforcement of suboptimal strategies (Erev and Roth (1998), Camerer and Ho (1999)).

The design of an institution that eliminates deviations from fundamental value in the laboratory remains an open task for economists. Our results are useful in that regard since they show for the first time that an institutional change can drastically change the price patterns in long-lived asset markets—from positive deviations to negative deviations from fundamental value. That is, institutions matter for bubble formation. This stands in contrast to the intuition offered by most previous studies, which suggest that bubbles are robust to institutional changes. An implication of our results is that the exercise of designing an institution that induces prices to track fundamentals is a potentially fruitful endeavor.

Specifically, we believe that future institutional design might concentrate on the following issues. (1) The institution should facilitate the subjects' comprehension of the link between the expected future dividend stream and the current value a rational trader places on the asset. The theoretical connection between dividends and willingness-to-pay, which is obvious to economists, appears not to be evident to some people. (2) The institution should ensure that participants are not making trades because of experimental demand effects. The remarkably high volumes observed in asset market experiments appear in part to be due to the lack of alternative activities (Lei et al. (2001)). (3) The institution should provide a mechanism that makes it common knowledge to

[15] Caginalp et al. (2000) estimate that each dollar of available cash raises the price of the asset by about 29 cents.

market participants that traders are using the expected future dividend stream as their limit price.

Short selling is ubiquitous in the world's financial markets. If restrictions on short sales are tight, investors who are bullish on a stock will buy it, but few who are bearish will sell it short.[16] In the absence of short selling, the asset price will simply be the price offered by the most optimistic trader with sufficient funds. With short selling, pessimistic traders are able to drive down the price. In principle, if traders' beliefs are distributed with a mean at the fundamental value of the asset, the price should closely track that fundamental value. However, our data suggest a possible shortcoming of short selling. It may overcompensate for bubbles and lead to prices lower than fundamental values. In financial asset markets, this could translate into a misallocation of capital. Our results suggest that institutional changes can affect bubbles, and that the efficacy of short selling depends on the limits and restrictions on its use and the proportion of traders using different classes of behavioral strategies. As such, the relationship between laws and regulations that restrict short selling and asset market bubbles merit careful investigation.[17]

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[16] For small investors, these restrictions include the requirement to deposit collateral and having the proceeds of the short sales held in escrow, earning little or no interest. Regulations against short selling on a downtick and the requirement to have actual shares to borrow are other restrictions. The recent dividend tax cut enacted in the United States poses another restriction for short sellers. Dividends paid by short sellers do not qualify for the dividend tax cut.

[17] The U.S. Securities and Exchange Commission, the New York Stock Exchange, and the National Association of Securities Dealers all place restrictions on short selling.

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