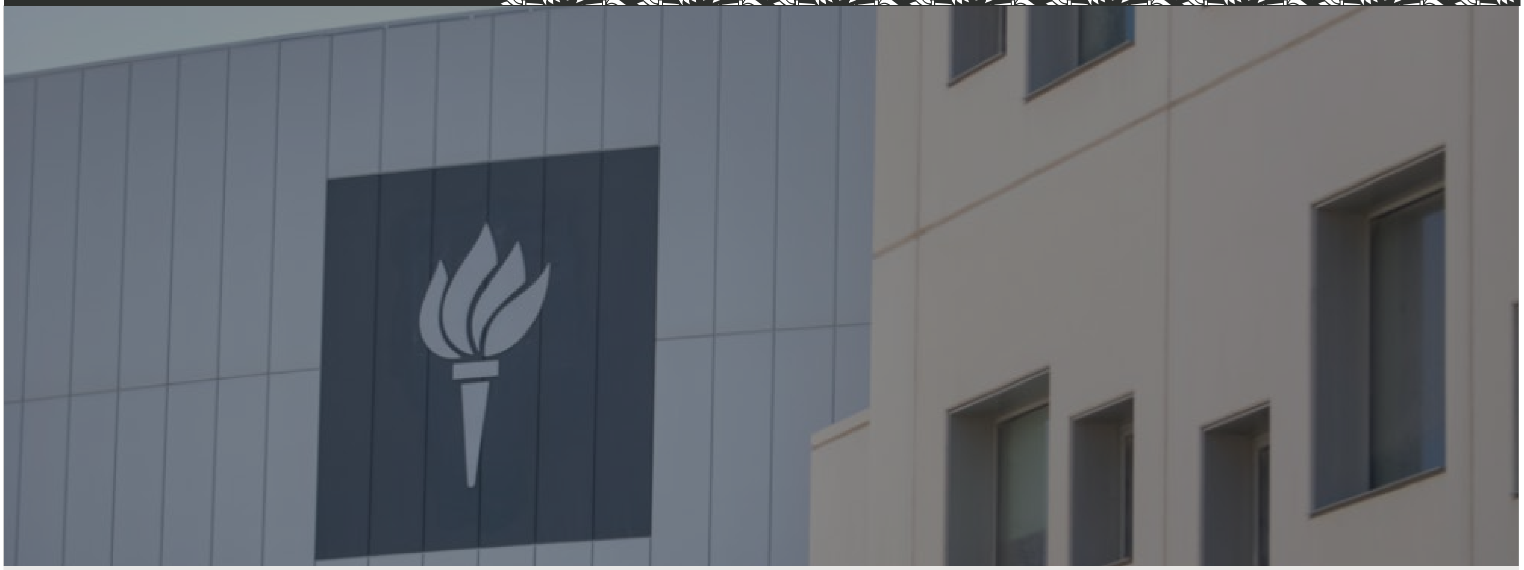

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Jacopo Magnani and David Munro

Working Paper # 0018
May 2018

Division of Social Science Working Paper Series

New York University Abu Dhabi, Saadiyat Island P.O Box 129188, Abu Dhabi, UAE

https://nyuad.nyu.edu/en/academics/divisions/social-science.html

Dynamic Runs and Circuit Breakers: An Experiment*

Jacopo Magnani† David Munro‡

May 15, 2018

Abstract

Although now widespread in financial markets, circuit breakers remain controversial among researchers and professional investors. We formalize the popular argument that circuit breakers provide a "cooling-off" period for investors during market runs and we test it in the laboratory. Our experiment reproduces a market where investors fear future liquidity shocks but receive news about the true state over time. Notably, we find that when information quality is poor circuit breakers can have perverse effects on trading behavior. However, when information quality is high, circuit breakers can improve welfare by providing agents with time to learn about the true state, when private incentives to wait for more information are insufficient.

Keywords: circuit breakers, market runs, experiment.
JEL Codes: G02, G18, G01.

*We thank seminar participants at the Bay Area Behavioral and Experimental Economics Workshop, Chapman University, the 2017 Southern Economic Association Meetings, the 17th Trento Summer School, the 8th Workshop on Theoretical and Experimental Macroeconomics at Stony Brook, and Xavier University. We are especially grateful to Dan Friedman for useful conversations and encouragement and to Christina Louie for excellent research assistance. We acknowledge funding from the National Science Foundation [Grant SES 1260813].

†Division of Social Science, NYU Abu Dhabi, Abu Dhabi, United Arab Emirates *jacopo.magnani@googlemail.com*

‡Corresponding author, Department of Economics, Middlebury College, 14 Old Chapel Rd., Warner Hall 505, Middlebury, VT 05753. *dmunro@middlebury.edu*

1 Introduction

Financial market volatility can have important welfare implications.[1] In recent decades, mandated trading halts, dubbed "circuit breakers," have become official policy for most major financial markets, with the aim of curbing financial instability. In the US, market-wide circuit breakers became widespread after the stock market crash of October 1987 and the Brady report (1988). They have been recently extended after the May 6, 2010 Flash Crash (as discussed in Angstadt, 2011).

Circuit breakers can be a desirable policy if they prevent "unnecessary" market volatility and the welfare costs associated with this volatility. Thus the key to understanding whether these policies are beneficial involves understanding how circuit breakers interact with trading decisions of investors and why trading behavior can potentially lead to excess price volatility when such policies are absent.[2] In this paper we attempt to shed light on these questions and explore the potentially beneficial role of circuit breakers during financial market runs. We formalize the popular argument that circuit breakers provide a "cooling-off" period for investors during market runs and thus provide a theoretical grounding to help understand why circuit breakers may prevent market volatility.

To help build intuition for why this is, consider the following scenario. A set of investors is exposed to a financial shock, e.g., via counter-party risk. At time 0, public news reveals a particular shock, such as a default of a major financial institution. There are two possible outcomes of this event. In the bad state, investors will have to liquidate a traded asset because the shock impairs their personal portfolio. In the good state, investors will turn

[1]Some prominent reasons for welfare costs of asset price fluctuations include financial frictions (e.g. Bernanke and Gertler, 1990), bankruptcy costs/organizational capital (e.g. Diamond and Dybvig, 1983), financial contagion (e.g. Allen and Gale, 2000), and heterogeneous preferences of market participants (e.g. Bernardo and Welch, 2004).

[2]Since the Flash Crash there has been a growing discussion about the need for circuit breakers in response to the increased use of algorithmic and high-frequency trading. In this paper we focus on the behavioral reasons why circuit breakers may be beneficial and thus potentially add very little to the discussion regarding market volatility and algorithmic trading. Insofar as the behavioral aspects we investigate are incorporated into automated trading rules or there is some interaction between the price effects of algorithmic trading and the behavioral response of human traders, our paper may be related to that discussion, however, we do not attempt to address these issues here.

out to be virtually unharmed. News about the state arrives gradually over time. Initially investors do not know whether they will be forced to liquidate. On the other hand, investors know from time 0 that in the bad state forced sales (liquidation) will lower asset prices and it is advantageous to preempt the market and sell before that happens in order to obtain a better price. This selling generates a negative externality on the salvage values for the remaining investors. If the early news is sufficiently bad, there can be a "run" as investors attempt to lock in superior prices and the asset is sold by all investors, although more accurate news may subsequently reveal that their portfolios are unharmed. Thus agents may act precisely when the reliability of their information is lowest because private incentives are insufficient to ensure that the market waits for an efficient amount of information about the value of the asset. In these circumstances, a temporary halt in trading may eliminate the inefficiency caused by early liquidations when the state is good by allowing agents more time to accumulate information about the true state of the world.

We test this hypothesis in a laboratory experiment that reproduces an illiquid market where stochastic information arrives over time. Our experiment compares laboratory financial markets with and without circuit breakers in two different information settings: a setting with highly informative signals where beliefs converge quickly over time and thus a temporary trading halt theoretically should succeed in restoring financial stability, and another where signals are less informative and circuit breakers are expected to fail. These predictions are drawn from a model based on rational agents and we study whether they are robust to the actual behavior of human subjects.

We find that, consistent with the basic intuition behind our model, subjects choose to liquidate inefficiently early on average. We also find evidence that in some sessions circuit breakers induce subjects to liquidate their assets earlier than in markets where there are no circuit breakers. However, this is true only in markets with relatively more noisy signals. When the quality of signals is high, the timing of liquidation decisions is not affected by whether the market is endowed with a circuit breaker or not. Finally, we find that circuit breakers reduce subjects' welfare in the low information environment, but increase welfare in the high information environment.[3] These findings are consistent with the notion that a market halt can be useful in that it allows more time for information to accrue when private incentives to wait for that information are insufficient. However, this will only be the case when the information revealed during the halt is of sufficiently high quality.

Our paper contributes to the large literature trying to evaluate the effects of circuit breakers. Some of the early empirical findings, surveyed in Kim and Yang (2004), are rather ambiguous: on the one hand trading halts do not calm the halted securities (in terms of activity and volatility), but on the other hand they seem to promote information transmission (Kim and Yang, 2004, p. 132). More recently, a number of empirical papers have suggested that trading halts improve order flow, liquidity, information dissemination and price discovery (see for example Corwin and Lipson (2000), Chakrabarty, Corwin and Panayides (2011), Engelen and Kabir (2006), Hauser, Kedar-Levy, Pilo and Shurki (2006), Madura, Richie and Tucker (2006)).

Lab experiments can complement field data studies on circuit breakers in two ways. First, lab experiments allow the researchers to evaluate whether trading halts are desirable by comparing identical markets with and without circuit breakers. As noted by Corwin and Lipson (2000, p. 1773) the central problem when using field data is that "we cannot know what would have occurred in the absence of a halt or what equilibrium trading patterns would be in a market where halts are not permitted." Second, lab experiments allow the researcher to quantify (and manipulate) the information available to the market participants, while quantitative measures of information cannot be directly observed in real-world markets (and are usually proxied by the endogenous response of market statistics such as trading volume).

Previous lab experiments on circuit breakers (Ackert, Church and Jayaraman (2001) and Ackert, Church and Jayaraman (2005)) have studied laboratory markets where an asset

[3]Later in the paper we highlight the connection between subject welfare and social welfare and thus, whether our findings should be interpreted as providing economic rationale for circuit breaker policies in financial markets.

with a common (but uncertain) final dividend is traded and in certain periods a subset of traders are informed about the distribution of the dividends. These studies find that circuit breakers are not effective in reducing deviations of prices from fundamentals and may accelerate trading activity when an interruption is imminent. Our experiment differs from these existing experiments in several ways, but two substantial differences are that 1) the market is prone to runs induced by liquidity concerns and 2) information accrues over time, even when trades are halted. We view this setting as desirable as it can capture the interactions between market-runs, information acquisition, and the potential role circuit breakers may play in reducing financial market volatility. Indeed, in describing the benefits of circuit breakers, the Brady Report states that they "facilitate price discovery by providing a "time-out" to pause, evaluate, inhibit panic, and publicize order imbalances to attract value traders to cushion violent movements in the market" (Brady Commission, 1988, p. 65).[4]

Our paper also contributes to the literature studying financial runs in the lab (see for example Schotter and Yorulmazer (2009), Madies (2006), Arifovic, Jiang and Xu (2011), Cheung and Friedman (2009)). To our knowledge, we are the first to develop a laboratory test of the market runs model of Bernardo and Welch (2004), a framework that is particularly useful for analyzing the role of circuit breakers. Our work is also related to the experiments on clock games by Brunnermeier and Morgan (2010). In clock games, agents receive differently-timed private signals when an asset value is above its fundamental and the price crashes to the fundamental when a fixed number of agents have decided to sell. One important difference between this framework and our experiment is that while in clock games each player acts *after* receiving his private signal, in our market game players do not wait long

[4] Although the connection between circuit breakers and financial runs has played an important role in the historical rationale for these policies (see Brady Commission (1988)), it has not been a major focus of the theoretical literature. Seminal contributions in the theoretical literature focused instead on the potential role of circuit breakers in reducing transactional risk and smoothing the lumpy price adjustments that arise from the market microstructure (Greenwald and Stein, 1991; Kodres and O'Brien, 1994). In concurrent work, Draus and Van Achter (2016) analyze the role of circuit breakers in curbing market runs. Like Draus and Van Achter (2016) we build on the market run model of Bernardo and Welch (2004). Our theoretical framework differs from theirs in that the model is dynamic and thus allows information to accrue over time and allows traders to chose precisely when, if ever, they wish to liquidate.

enough for information and this creates scope for a welfare-improving trading halt. Finally, in concurrent work, Kendall (2015) also studies trading panics in a laboratory market where information is received over time. However, while in Kendall (2015) subjects receive private signals about the asset fundamental value, in our experiment subjects receive signals about an impending shock to market liquidity as in the Bernardo and Welch (2004) framework.

The rest of the paper is organized as follows. In Section 2 we present the theoretical framework. In Section 3 we describe the experimental design and hypotheses. In Section 4 we present the results and Section 5 concludes.

2 Theoretical Framework

In this section we describe the theoretical framework of our experiment. The modeling approach we choose is motivated by an attempt to capture the following important aspects of the market environment surrounding a circuit breaker: a) It is an environment where a rapid sell-off is possible. Thus, for tractability reasons the model abstracts, through a market maker, from the buyers' side of the market; b) There is uncertainty about the value of the asset and this information accrues over time; c) It is an environment where traders have an incentive to "beat the market" if asset values are low, thus generating the possibility for market runs to occur; and finally, d) Traders are able to choose exactly when they wish to sell, so the model is dynamic. In Section 2.1 we introduce this dynamic version of the Bernardo and Welch (2004) model. In Section 2.2 we discuss the welfare maximizing liquidation rule and argue that in the equilibrium space of this market game investors liquidate inefficiently early. In Section 2.3 we discuss the potential role of circuit breakers in increasing investor welfare in this framework.

2.1 The Market Model

Time is discrete, $t \in \mathbb{N}$. The game ends at a random date that follows a geometric distribution with probability of termination λ. There are N risk-neutral investors who discount consumption at a rate β. Each investor is endowed with a unit of an asset. Investors can sell the asset at any time before the game ends, but the decision to sell is irreversible.

There are two states of the world, $s \in \{B, G\}$. In the bad state (B) the investor community is hit by a liquidity shock and in the good state (G) investors are safe. When the game ends, all investors that are still holding the asset receive the asset return, equal to v, if $s = G$ and they are forced to liquidate at the market price if $s = B$. As in the financial runs literature (e.g. Diamond and Dybvig (1983), Bernardo and Welch (2004)) we do not specify the reason why investors expect a liquidity shock. In general, this could happen if the investor has to re-establish appropriate margin, liquidate collateral or fulfill a previously contracted payment when some event occurs.

Let p_k be the market price for a share when the inventory of shares already held by the market is k. We call $\{p_k\}_{k=0}^{N-1}$ the price schedule. If a group of $M > 1$ investors sell at the same time, the market uses a tie-breaking rule, ordering the M investors from first to last with equal probability and then executing orders sequentially. We make the following assumption about the price schedule:

$$v > p_0 > p_1 > ... > p_{N-1} \tag{1}$$

This assumption represents the usual notion of illiquidity: the act of selling causes a fall in the price. As in Bernardo and Welch (2004), the price schedule can be derived from the assumption of a risk-averse competitive market-maker who absorbs shares upon demand. In particular, we will assume a price schedule of the form:

$$p_k = v - a - bk \tag{2}$$

where a and b are positive parameters. A price schedule of this form can be obtained from a CARA utility market-maker, as discussed in Appendix A.

There is uncertainty about the state of the world. Investors start the game with a common prior belief about s: $\pi_0 \equiv Prob[s = B]$. From the start to the end of the game, a flow of stochastic information is gradually revealed to the public. Agents observe a public signal at each date that is either "bad" or "good", $Y(t) \in \{b, g\}$. Because information is public, all agents in a market observe the same signal. The likelihood of a bad signal is: $\mu_G = Prob[Y(t) = b|s = G]$ and $\mu_B = Prob[Y(t) = b|s = B]$, $\mu_B > \mu_G$. We will also assume the normalization: $\mu_B + \mu_G = 1$. The posterior probability is given by:

$$\pi(t) \equiv Prob[s = B|Y(t), \pi(t-1)] = \begin{cases} \frac{\pi(t-1)\mu_B}{\pi(t-1)\mu_B + (1-\pi(t-1))\mu_G} & \text{if} \quad Y(t) = b \\ \frac{\pi(t-1)(1-\mu_B)}{\pi(t-1)(1-\mu_B)+(1-\pi(t-1))(1-\mu_G)} & \text{if} \quad Y(t) = g \end{cases}$$

The posterior probability is a martingale with respect to the filtration generated by $\pi(t)$, that is: $E[\pi(t)|\pi(s)] = \pi(s)$, $t \geq s$. By the Martingale Convergence Theorem, the posterior belief converges almost surely to 1 if the true state is B and to 0 if the true state is G. In practice, convergence will be faster the larger the signal-to-noise ratio, defined as: $\text{SNR} \equiv \frac{\mu_B - \mu_G}{\mu_B \mu_G}$. Figure 1 illustrates some sample paths of the posterior belief in different states of the world and for different values of the signal-to-noise ratio. The prior used in these examples is $\pi_0 = 0.5$.

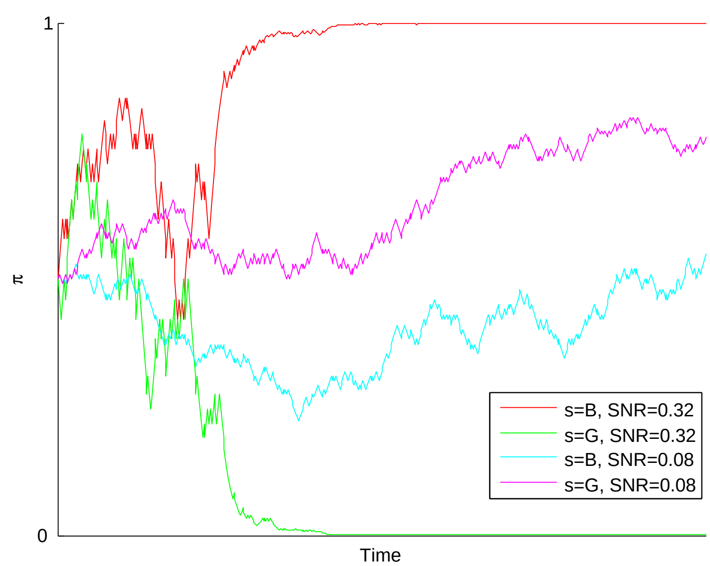

Figure 1: *Some sample paths for different* π *processes*

2.2 Optimal Liquidation

At this point, we are able to solve for the efficient liquidation rule that maximizes the welfare of the investors. In order to derive this rule, the externality generated by one investor's sale on the other investors' salvage values is internalized. This is the case where one investor, say a mutual fund, owns all the shares. The optimal rule involves liquidating all the shares at the same time, for an average price of $p^m \equiv \frac{1}{N}\sum_{k=0}^{N-1} p_k$. Let $V(\pi)$ be the value of the option to wait to sell the assets when the posterior probability is π. This value is determined in the following way. First, in the current period with probability λ there is a liquidity shock. In this case all the investors are forced to sell at the average price p_m with probability π and they are rewarded the asset value v with probability $(1-\pi)$. If the liquidity shock does not occur, with probability $(1-\lambda)$, the investors receive the discounted value of the end-of-period payoffs. The latter are determined in the following way: the mutual fund can choose between liquidating the shares at p_m or obtaining the expected continuation value $E[V(\pi')|\pi]$. Thus the value of the option to wait to sell the asset satisfies the Bellman equation:

$$V(\pi) = \max\{p^m; W(\pi)\}$$
$$W(\pi) = \lambda[\pi p^m + (1-\pi)v] + (1-\lambda)\beta E[V(\pi')|\pi]$$

where $W(\pi)$ is the continuation value. Let τ_{eff} be the value of π such that $p^m = W(\pi)$. The efficient liquidation rule is to sell at time $t_{\text{eff}} \equiv \inf\{t : \pi(t) = \tau_{\text{eff}}\}$. Figure 2 illustrates the optimal solution of the mutual fund's problem.

The special case $\beta = 1$ is represented in Figure 2b. Because of its simplicity, in our lab implementation we focus on this case. In this case investors are patient and therefore the efficient solution for the fund's manager is to wait until she is certain that the state is bad, which occurs only in the limit $t \to \infty$. Therefore when $\beta = 1$ the efficient strategy involves holding on to the assets until the game ends. In this case, the value of the mutual fund is the weighted average of the final payoffs in the two states, with the state beliefs as weights. If the state is good then the value of the fund is equal to the asset return, v, and if the state

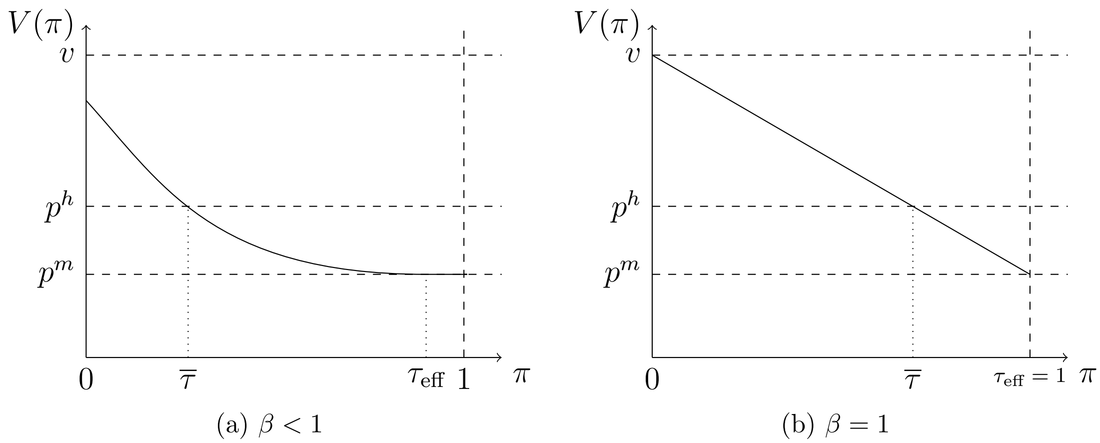

Figure 2: *The efficient liquidation rule*

is bad, then the value of the fund is just the average liquidation value, p^m:

$$V(\pi) = (1 - \pi)v + \pi p^m$$

and the efficient liquidation thresholds is $\tau_{\text{eff}} = 1$.

The efficient solution involves holding on to the assets until a sufficient amount of bad news has accumulated. Because there is an advantage in liquidating before others, individual investors do not have the incentives to wait until the efficient threshold is reached. It is easy to show that τ_{eff} is not an equilibrium. Denote the price that the first investor obtains by liquidating ahead of all the others by $p^h = \max\{p_k\}$. Assume $N-1$ investors are committed to liquidate at τ_{eff}. Note that in this case, the value of holding on to the asset is equal to the mutual fund's value, $V(\pi)$. As π increases, the value of holding on to the asset becomes closer to p_m. However, the N-th investor can guarantee himself a payoff of $p^h > p^m$ by liquidating first. This is illustrated in Figure 2: the best response of the N-th investor is to liquidate as soon as the belief reaches $\overline{\tau}$, where $V(\overline{\tau}) = p^h$, that is:

$$\overline{\tau} = \frac{v - p^h}{v - p^m}$$

The best reply to liquidation at the efficient threshold involves preempting the other investors: $\overline{\tau} < \tau_{\text{eff}}$.

Note that it may not be an equilibrium for all the investors to liquidate at $\overline{\tau}$. Figure 3 illustrates a situation where liquidating at $\overline{\tau}$ is not an equilibrium. To see why, assume $N-1$ investors are committed to liquidate at $\overline{\tau}$ and consider the two choices of the N-th investor: joining the run or waiting. If the N-th investor joins the run, then his expected payoff is p^m. If he waits, then in the good state he obtains the asset return, v, and in the bad state he obtains the lowest liquidation value, $p^l \equiv \min\{p_k\}$. Thus the value of waiting for the last investor is: $U(\pi) = (1-\pi)v + \pi p^l$. When the value of waiting at the run threshold is larger than the average liquidation value, $U(\overline{\tau}) > p^m$, then the best response of the N-th investor is to not join the run. While not all the investors will run on the market at $\overline{\tau}$, we know that at least one investor will liquidate before or at the first hitting time of $\overline{\tau}$. We also know that no investor will liquidate before the first hitting time of a lower threshold, $\underline{\tau}$. Below this threshold, the belief of a forced sale is so low that even the value of being the last investor in the market is larger than the highest liquidation value. Formally, at the lower threshold we have: $U(\underline{\tau}) = p^h$ and thus:

$$\underline{\tau} = \frac{v - p^h}{v - p^l}$$

In the parametrization we use in our experiment, these arguments imply that we expect the first liquidation decision to occur when beliefs are in the range $0.67 - 0.8$.

2.3 Welfare and Circuit Breakers

Early sales cause a loss in the investors' welfare, as investors will end up forgoing the good-state payoff too often. In the case of patient investors ($\beta = 1$) that we induce in the lab, the rule that maximizes investor welfare involves holding on to the assets until the game ends. Under the assumption that the market maker is risk-averse, this rule maximizes not only investor welfare but also total market welfare. As in Bernardo and Welch (2004), it is efficient for patient investors to sell to the market-making sector only when they are actually hit by a liquidity shock, otherwise risk neutral investors are giving risky assets to the risk

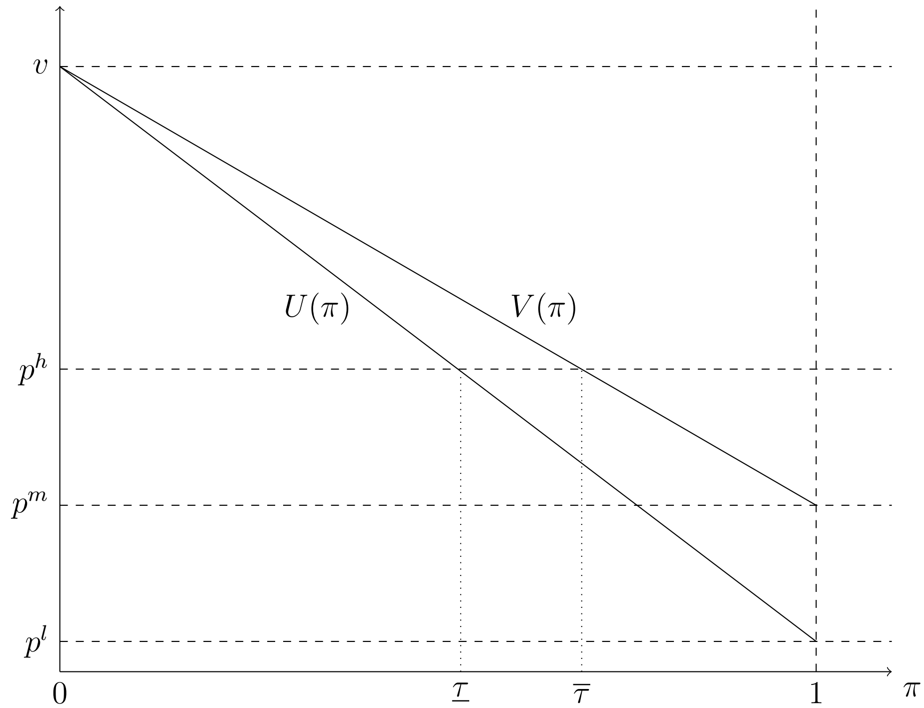

Figure 3: *Liquidation thresholds*

averse market-maker.[5]

In these circumstances, a temporary halt in trading may eliminate the inefficiency caused by early liquidations when the state is good. A circuit breaker operates by providing agents with time to gain more information about the true state, when private incentives to wait for better information are insufficient. Critically, the effectiveness of a circuit breaker depends on whether players are likely to receive useful information during the trading halt. As illustrated in Section 2.1 the speed at which posterior beliefs converge to the true state is measured by the signal-to-noise ratio. Thus when SNR is higher, investors are more likely to revise their beliefs in the right direction during a market freeze of a given length.

As suggested by Subrahmanyam (1994), a temporary trading halt may have perverse effects on the investors' decisions. In our framework, investors may rush to liquidate earlier

[5]As highlighted in an earlier footnote, the particular reason why liquidations are socially costly in Bernardo and Welch (2004) (heterogeneous preferences of market participants) is not the only reason why one should be concerned with widespread selling of an asset. Some other prominent reasons why market runs are socially costly include financial frictions, bankruptcy costs or organizational capital concerns, and contagion, among others. We make this point to emphasize that investors' welfare is a sufficient metric in this setting to draw general conclusions about the social welfare implications of circuit breakers.

when they are aware of a circuit breaker rule. While we do not attempt to analyze the mechanism that may lead investors to behave in this way, our framework allows us to model the magnet effect as a decrease in the liquidation threshold $\overline{\tau}$. In turn, a lower $\overline{\tau}$ leads to lower welfare on average. Thus, whether a circuit breaker increases or decreases welfare depends on how it affects investors' behavior and its interaction with the information structure.

3 The Experiment

In Section 3.1 we describe our laboratory implementation of the model. In Section 3.2 we discuss our treatment design and hypotheses. In Section 3.3 we give details on how the experiment was conducted.

3.1 Implementation

v	p_0	p_1	p_2	p_3	λ	π_0	μ_B^{HIGH}	μ_G^{HIGH}	μ_B^{LOW}	μ_G^{LOW}
20	8	6	4	2	0.125	0.5	0.675	0.325	0.53	0.47

Table 1: *Parameter values*

In our experiment subjects play the market game described in Section 2. The parameter values we used in the experiment are listed in Table 1. Each market consists of $N = 4$ subjects, randomly matched into groups. The asset value in the good state is $v = 20$. The market price is given by a linear price schedule with $p_0 = 8, p_1 = 6, p_2 = 4, p_3 = 2$. Information within each round is updated in 4 second intervals, but subject actions and the asset's price are updated in real-time.[6] The length of each round is drawn independently from a geometric distribution with minimum round length equal to eight seconds and probability of termination $\lambda = 0.125$. This implies the average length of a round is 32 seconds.

[6]The time interval between one signal and the next in our experiment is long enough for subjects to respond to the new information. Existing evidence from other near-continuous time experiments, such as Brunnermeier and Morgan (2010), suggests that subjects, on average, take only a fraction of a second to respond to relevant changes in the environment.

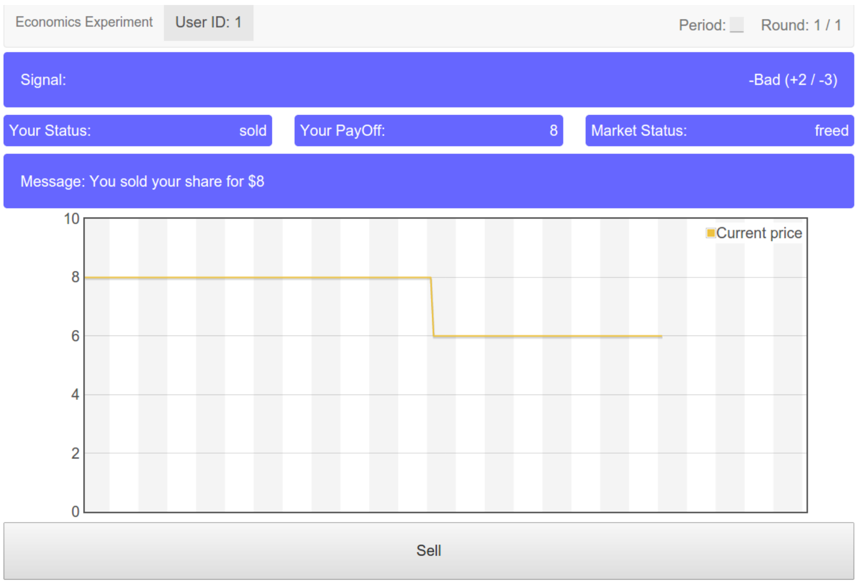

Figure 4: *Example user interface*

In each round the state is either B or G, with equal probability. A public signal about the actual state of the market arrives every 4 seconds. In each round the subject display, reproduced in Figure 4, shows the current tally of signals, the current market price, and for CB treatments whether market trading is frozen. Because the information is public, all subjects in a market observe the same signals. The price is updated in real time. A subject's only decision is when, if ever, to press a button labeled "Sell." The experiment is run with a semi-strategy method, showing the information accumulated up to termination even after all subjects sell. The state, the realization of signals, and the actual value of the round ending time are drawn randomly in advance. After the round is over, each subject is shown a summary message showing: 1) her score in the round, 2) whether she sold her share by clicking on the button during the round, 3) how the round ended: Forced Sale or Payout. The break between rounds lasts around 10 seconds.

3.2 Design and Hypotheses

In our experiment early sales are inefficient. Indeed, since our experiment matches the $\beta = 1$ case discussed in Section 2.2, the welfare maximizing rule is for subjects to liquidate only when the posterior belief has asymptotically converged to $\tau_{eff} = 1$, independently of the parameters of the game.[7] However, our theory predicts subjects will liquidate inefficiently early. In particular, the discussion presented in Section 2.2 suggests the following:[8]

Hypothesis 1. *The first liquidation decision occurs in the interval* $[\underline{\tau}; \overline{\tau}] = [0.67; 0.8]$.

We designed the treatments of our experiment to identify how circuit breakers affect liquidation decisions and exactly in which conditions, if any, they can improve welfare. However, given the small size of these laboratory markets, designing a CB trigger rule to reflect those used in actual financial markets is not without issue.[9] We instead attempt to capture the key market dynamics that lead to a trading halt. In CB sessions, subjects are informed that the market will freeze when too many players sell their stocks in a short time horizon. Specifically, if two or more players attempt to sell their stocks within 3 seconds of each other the market will freeze.[10] For example, if one player decides to sell their stock that transaction will be executed. For 3 seconds after this first transaction, if another player attempts to sells their stock the market will freeze for all the remaining subjects. During a market freeze sell buttons are disabled. The market unfreezes after 10 seconds at which point any participant who still owns a stock is again able to sell it if they choose to. The market can only freeze once per round. Subjects are notified when the market is frozen. In NoCB sessions the market is not endowed with a circuit breaker. Our theory predicts that subjects will attempt to liquidate inefficiently early in all markets and previous research suggests that circuit breakers may aggravate this problem, causing subjects to try to liquidate even earlier.

[7]Note that we do not induce time discounting in the lab and the actual time preferences of subjects do not affect decisions in this task because all dollar payments occur at the end of the experiment. One could induce time discounting, and thus have $\tau_{eff} < 1$, by introducing a third, 0 payoff, state. We felt this added a complication to the experiment without providing an obvious benefit.

[8]The predictions in Hypothesis 1 were derived under the assumption of risk neutrality and are not robust to the actual risk preferences of our laboratory subjects. For example, risk aversion could cause the first liquidation decision to occur at beliefs lower than predicted by Hypothesis 1. Thus, the threshold in Hypothesis 1 may overstate what we should expect insofar as the average subject is risk averse. We discuss this in the results below.

[9]As an example of an actual trigger rule, current SEC regulations stipulate that if the S&P 500 falls more than 7% from the previous days close (a "Level-1" decline), a market wide trading halt will be triggered.

[10]These two sales represent a 50% price decline in our experiment, well beyond the decline required in SEC regulations.

From this we formulate our next hypothesis:

Hypothesis 2. *The first liquidation decision occurs earlier in CB sessions than in NoCB sessions.*

How will circuit breakers affect welfare? As discussed above the welfare effects of circuit breakers are likely to depend on the information environment. Therefore we conducted sessions where the information content of the signals is low (LOW sessions) and sessions were the information content is high (HIGH sessions). In LOW sessions the probability of receiving a correct signal at each update is only 0.53, while in HIGH sessions the probability of receiving a correct signal at each update is 0.675. We calibrate these parameters in such a way that beliefs are significantly more likely to be updated towards the true state in HIGH sessions than in LOW sessions during a market freeze lasting 10 seconds and containing two information updates. Specifically, in LOW sessions the two signals subjects receive during a market freeze are contradictory (one b signal and one g signal) with a probability of almost 0.5, while the probability that both signals are consistent with the true state (e.g. two b signals when the state is B) is only around 0.28. By contrast, in HIGH sessions receiving two correct signals is the most likely outcome and occurs with probability around 0.46.

Thus we hypothesize that the circuit breaker rule will be ineffective in reducing the number of inefficient sales in LOW sessions, but will improve players' welfare by reducing the number of inefficient sales in HIGH sessions by allowing them more time to gather high quality information during the market freeze. We summarize this discussion in the following hypotheses:

Hypothesis 3. *Welfare in the CB-LOW treatment is less than or equal to the NoCB-LOW treatment.*

Hypothesis 4. *Welfare in the CB-HIGH treatment is higher than in the NoCB-HIGH treatment.*

3.3 Details

We implemented the experiment using a custom piece of software programmed in a new Javascript environment called Redwood (Pettit, Hewitt and Oprea, 2014). Data was collected in the LEEPS laboratory at the University of California, Santa Cruz between January and February 2015. A total of 80 subjects were drawn from an undergraduate subject pool using students from across the curriculum, recruited using the ORSEE software (Greiner, 2015). Subjects were randomly assigned to visually isolated terminals and interacted with no other subjects during the session. Instructions were read aloud prior to the beginning of the experiment and a quiz was administered to ensure subject comprehension. Both are reproduced in the Online Appendix. Subjects were paid a $7 show-up fee and the sum of points earned over all periods converted at an exchange rate of 55 points to 1 Dollar. Sessions lasted roughly 1 hour including instructions and subject earnings averaged approximately $17.

4 Results

In Section 4.1 we analyze the subjects' liquidation decisions in the belief space and show extensive evidence of inefficient early sales. Using data on beliefs at the first sale in each market we test whether circuit breakers have perverse effects on liquidation decisions but fail to find any effect. In Section 4.2 we repeat this test using data on the actual time of sales and show evidence suggesting circuit breakers induce investors to advance liquidation decisions in time, at least in some treatments. In Section 4.3 we show that circuit breakers decrease investor welfare in LOW sessions but increase it in HIGH sessions. In Section 4.4 we document how circuit breakers induce clustering of sales after a trading halt.

4.1 Liquidation Decisions and Beliefs

We begin by examining the level of the posterior belief π at the time of the first sale in each round. In order to study how the threshold belief used by subjects varies across treatments we run the following regression:

$$BeliefFirstSale_{it} = \alpha_{0,t} + \alpha_1 CB_{it} + \alpha_2 LOW_{it} + \alpha_3 CB_{it} * LOW_{it} + error_{it}, \tag{3}$$

Belief at First Sale	Coeff.	Std. Err.	P-Value
CB	0.018	0.016	0.282
LOW	-0.063	0.013	0.000
CBxLOW	-0.023	0.017	0.171
Cons.	0.581	0.012	0.000

Table 2: *Reports regression results from specification* (3)*. The regression includes round fixed effects. There are 741 observations and the regression has an* $R^2 = 0.069$*. Robust standard errors are reported.*

where $BeliefFirstSale_{it}$ is the level of the posterior belief π at the time of the first sale in round t of market i, $\alpha_{0,t}$ are round fixed effects,[11] CB_{it} is a dummy variable equal to one in CB sessions and LOW_{it} is a dummy variable equal to one in LOW sessions. The regression results, reproduced in Table 2, show that the first liquidation decision occurs on average at a value of π equal to 58% in NoCB-HIGH sessions. The threshold belief for the first liquidation tends to be even lower, around 52%, in NoCB-LOW sessions, possibly because beliefs evolve more slowly in the LOW information environment.

Our estimates suggest subjects act on very poor information. Indeed the average belief threshold is below the lower bound $\underline{\tau} = 0.67$ suggested by our discussion of the model. As we mentioned above, risk aversion may be responsible for this. As in (Bernardo and Welch, 2004), investors are assumed to be risk neutral in the model. Risk averse agents would lower the thresholds $\underline{\tau}$ and $\overline{\tau}$ predicted by the theory.[12]

So far we have focused on cross-round average beliefs at the time of the first sale, but this masks potential learning during the experiment. Figure 5 and Figure 6 report the average

[11] In the experiment we kept the randomly drawn information sequences the same across the CB and NoCB sessions to allow for a mapping between the rounds. The round fixed effects will pick up the specific effects from the sequence of information that is identical between rounds.

[12] The structure of the experiment generates an interesting sampling issue. In many "good" rounds it is sensible to not sell with the positive information on asset values received, and thus no sale data is recorded by those sensible non-actions. However, subjects who do sell during those rounds do have sales recorded. This may bias the sample towards who are either extremely risk averse or unsophisticated traders. To shed light on this we also report results that use data from only "bad" rounds where it is more sensible for *all* subjects to trade. These results, reported in Table 5 in the Appendix, show that the beliefs at the first sale are higher and we fail to reject they are statistically different from $\underline{\tau}$ in the NoCB-HIGH sessions.

value of π for each round. Figure 5 shows that first sales at levels of π outside the probability threshold predicted by theory are much less likely later in the experiment.[13] Unlike the HIGH treatments, evidence of learning is very weak in the LOW treatments (Figure 6), which, again, may be related to the poor information quality in these treatments. Beliefs in these treatments rarely get far from 0.5 as the probability of receiving an accurate signal at each update is only 0.53.

While, in general, these first sales occur at beliefs that are slightly below the range predicted by the theory, what is important in the context of this paper is that these results show that subjects trade on very poor information, which leaves open the possibility for CBs to improve welfare by allowing for more time for information acquisition on asset values. We summarize these findings in the following:

Result 1. *The first trade occurs inefficiently early on average. Restricting attention to later rounds or bad state rounds, beliefs at the time of the first sale approach the predictions of our theory,* $\pi \in [0.67, 0.8]$*, in HIGH sessions. In LOW sessions, however, beliefs at the time of the first sale are persistently below the predicted lower bound.*

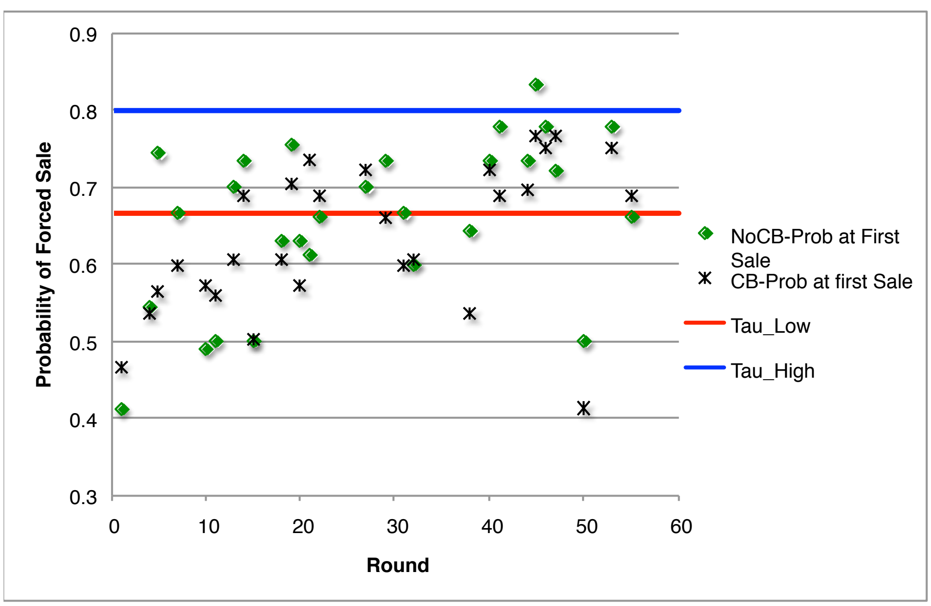

Figure 5: *Plots average value of* π *for each round in CB and No-CB treatments and thresholds predicted by theory :* $\overline{\tau}$ *and* $\underline{\tau}$*.*

[13]This is also confirmed by examining the regression results in Table 6 in the Appendix which is estimated using only rounds in the second half of the experiment.

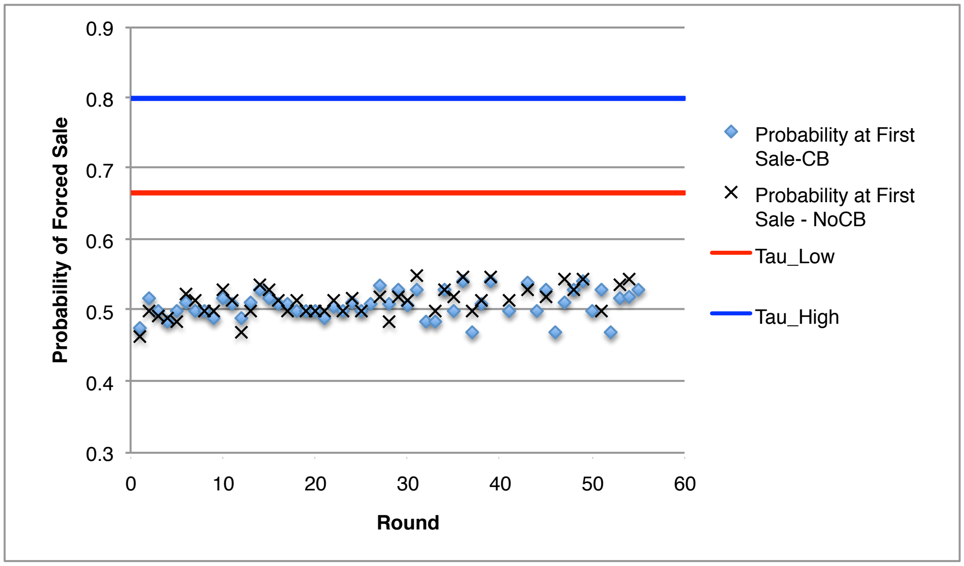

Figure 6: *Plots average value of π for each round in CB and No-CB noisy treatments and thresholds predicted by theory :* $\overline{\tau}$ *and* $\underline{\tau}$.

We observe no significant difference between CB and NoCB sessions in either the HIGH or LOW treatments. As both Table 2 and Table 5 show, coefficients for CB sessions are insignificant. Visual inspection of the data in Figure 5 and Figure 6 confirms that there is little difference between CB and NoCB sessions. Thus we fail to observe any perverse effect of circuit breakers on the belief threshold for early liquidations.

Result 2. *Early sales occur at similar beliefs across CB and NoCB sessions within the same information environment.*

4.2 The Timing of Liquidation Decisions

Subrahmanyam (1994) argues that a circuit breaker will cause a "magnet effect" causing traders to advance the trades in time to avoid being blocked by a market halt. In the previous section we fail to observe any perverse effect of circuit breakers on the belief threshold for early liquidations. Here we test this hypotheses by tracking the actual time (in seconds) of the first trade in each round and comparing this across CB and NoCB treatments using the following specification:

$$TimeFirstSale_{it} = \alpha_{0,t} + \alpha_1 CB_{it} + \alpha_2 LOW_{it} + \alpha_3 CB_{it} * LOW_{it} + error_{it}, \qquad (4)$$

Time (Seconds)	Coeff.	Std. Err.	P-Value
CB	−0.590	0.786	0.460
LOW	1.755	1.559	0.261
CBxLOW	−2.760	1.398	0.049
Cons.	6.595	1.054	0.000

Table 3: *Reports regression results from specification* (4). *The regression includes round fixed effects. There are 656 observations and the regression has an* $R^2 = 0.292$. *Robust standard errors are reported.*

Table 3 reports the regression results from specification (4).[14] We find that the average time at the first sale is lower in the CB sessions, but this difference is statistically significant only in LOW sessions. In LOW sessions, a circuit breaker causes subjects to execute the first sale around 3 seconds earlier than in a market without a circuit breaker. Thus, it appears that a circuit breaker can have a perverse "magnet effect" on trading behavior only in environments with poor information quality. We also find that the first sale occurs significantly later in LOW sessions compared to HIGH sessions. Thus subjects respond to the lower signal quality by waiting more before taking an action. We summarize our main finding on the timing of sales in the following:

Result 3. *The first trade occurs earlier in CB-LOW treatments than in NoCB-LOW treatments. However, there is no significant difference in the timing of first sales between CB-HIGH treatments and NoCB-HIGH treatments.*

4.3 Circuit Breakers and Investor Welfare

To examine whether circuit breakers improve efficiency we compute investor welfare in each round as the the value realized by the subjects relative to the total possible value. As noted above, under the standard assumptions of the Bernardo and Welch (2004) model, the market-making sector has zero expected utility gain, so a total welfare comparison only requires a comparison of the investors' utility. Thus the welfare loss from early liquidations can be measured by the difference between the payoff to the efficient rule (i.e. holding on

[14]Table 7 and Table 8 in the Appendix reports these results examining "bad" rounds only and rounds from the second half of the experiments, respectively.

the assets until the game ends) and the sum of payoffs realized by the investors given their individual liquidation strategies.

Denoting K as the number of subjects who decide to sell their shares or are forced to do so (if the state is bad), the total value realized in a market with N subjects is:

$$\sum_{k=1}^{K} p_{k-1} + (N-K)v \tag{5}$$

The maximized total value, achieved if subjects follow the efficient liquidation rule and hold on to their shares until the market game ends, is $\sum_{k=1}^{N} p_{k-1}$ in a bad state and Nv in a good state. In bad state rounds welfare is always 100% because every unit is ultimately sold, either voluntarily during the round or by force at the end of the round. As such, welfare can only be suboptimal in "good" rounds, where it is given by:[15]

$$\%Welfare \equiv \frac{\sum_{k=1}^{K} p_{k-1} + (N-K)v}{Nv} \tag{6}$$

To examine the effect that a circuit breaker has on investor welfare we run the following specification:[16]

$$\%Welfare_{it} = \alpha_{0,t} + \alpha_1 CB_{it} + \alpha_2 LOW_{it} + \alpha_3 CB_{it} * LOW_{it} + error_{it} \tag{7}$$

Regression results are reported in Table 4.

[15]By construction, our measure of relative welfare simply rescales the number K of shares sold before the end of a round when the state is good. This measure is equal to 100% if $K=0$, 85% if $K=1$, 67.5% if $K=2$, 47.5% if $K=3$ and 26.25% if $K=4$.

[16]In this analysis, the first 5 rounds of data are excluded to allow subjects to have time to become familiar with the trading environment. However, as is apparent in Figure 5, this learning may take long than 5 rounds. As such, we also compare the efficiency between the CB and NoCB treatments only examining the rounds in the second half of the sessions in Appendix B.

Efficiency	Coeff.	Std. Err.	P-Value
CB	0.067	0.019	0.000
LOW	0.359	0.048	0.000
CBxLOW	−0.123	0.023	0.000
Cons.	0.654	0.044	0.000

Table 4: *Reports regression results from specification* (7) *using all rounds. The regression includes round fixed effects. There are 490 observations and the regression has an* $R^2 = 0.396$. *Robust standard errors are reported.*

These results show that in the LOW treatment a circuit breaker reduces efficiency. We find that NoCB-LOW sessions produce an average efficiency that is 5.6% larger than the CB-LOW sessions.[17]

Result 4. *Welfare is lower in the CB-LOW treatment than in the NoCB-LOW treatment.*

In contrast to the LOW treatments where the circuit breaker reduced efficiency, in the HIGH treatment we find that CB sessions, on average, have an efficiency that is 6.7% larger than NoCB sessions and that this difference is statistically significant at the 1% level. Table 9 in Appendix B shows that the difference between the CB and NoCB treatments becomes stronger when examining only the second half of the data. Collectively, these results support the notion that circuit breakers can be beneficial through their interaction with information accumulation. When the quality of information is high, circuit breakers improve efficiency but when the quality of information is low, the additional signals gathered during the market halt is not informative and thus does not lead to an improvement in efficiency.

Result 5. *Welfare is higher in the CB-HIGH treatment than in the NoCB-HIGH treatment.*

4.4 Circuit Breakers and Clustering of Sales

While Subrahmanyam (1994) highlights one potential cost of circuit breakers, there is another worth highlighting in the context of this paper. In an environment where traders have

[17] This result, however, is not completely robust to learning, as examining the second half of the rounds only reduces this difference to 2.43% which fails significance at the 10% level. See Table 9 in Appendix B.

imperfect information about the value of assets, strong negative information will lead to rapid liquidations. While a circuit breaker may reduce the sale of valuable assets by giving agents more time to gather information, it may also be the case that further negative information accumulates during the market halt. In this case, the circuit breaker may result in a clustering of trades when the market re-opens as traders now have stronger negative beliefs about the asset than they did prior to the trading halt. We choose an example of this from the experiment and plot it in Figure 7. This figure depicts the evolution of the probability of a forced liquidation (given by the blue line) in a bad state round. The vertical lines show the time at which trades are entered to the market. After the third bad signal the first two sale attempts occur in rapid succession. The first sale is executed and the second triggers the circuit breaker, and is not executed. During the circuit breaker, more bad signals arrive and the Bayesian updated probability of a forced liquidation stands at over 95% by the end of the trading halt. When the market re-opens, two of the remaining traders rush to liquidate their assets as there is now a very high probability that the round will end poorly. In these sorts of cases a circuit breaker may induce a strong clustering of sales, when without a circuit breaker it is likely those sales would have taken place over a more dispersed time interval. The extent to which this clustering of sales may be undesirable is not necessarily obvious, as in our experiment there is no efficiency cost associated with sales in "bad" rounds. However, insofar as drastic price declines in short time intervals may have other undesirable consequences, perhaps through their interaction with other behavioral phenomenon such as herding or through their interaction with algorithmic trading, we view this potential side effect of circuit breakers as worth highlighting, and to our knowledge has not been highlighted in the literature to date.

5 Discussion

In this paper we explore the potentially efficiency-enhancing role of circuit breakers during financial market runs. We implement a laboratory experiment where subjects receive

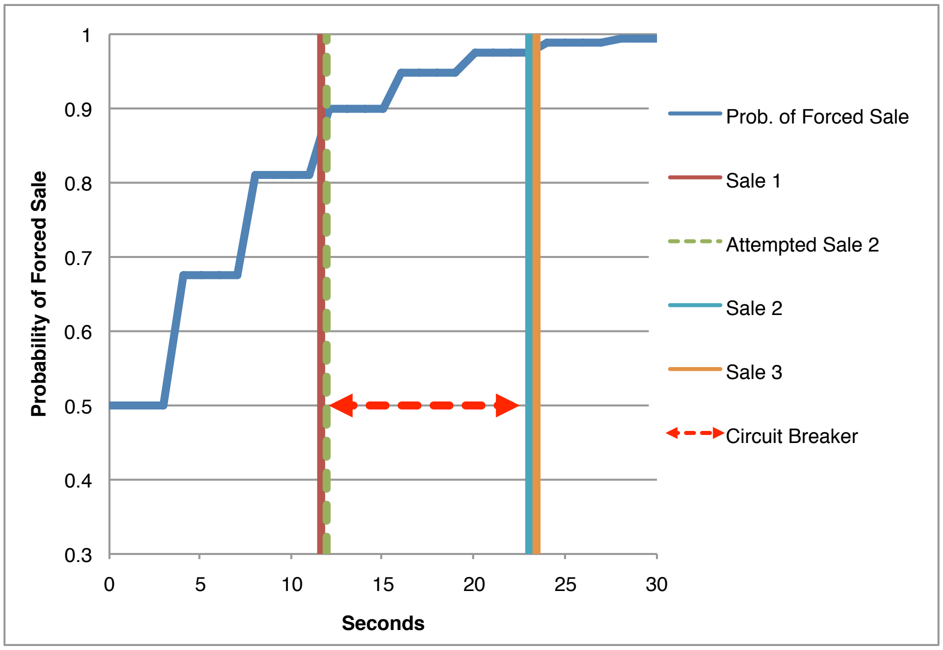

Figure 7: *Plots an example of the clustering of sales that follows a halt in trading*

stochastic news about the state of the market and choose when, if ever, to liquidate their assets. In these markets, when early news is sufficiently bad, there can be a "run" on the market, although more accurate news may subsequently reveal the state to be better than initially perceived.

We show that in our laboratory markets a temporary halt in trading can reduce the inefficiency caused by early liquidations when the state is good. A circuit breaker operates by providing subjects with time to digest news (i.e. gain more information about the true state), when private incentives to wait for better information are insufficient. Critically, our data show that the effectiveness of circuit breakers depends on the quality of signals. If the quality of information is high, we find evidence that a brief trading halt improves welfare. On the other hand, when the quality of signals is low, our data show that a circuit breaker can have perverse effects, inducing subjects to liquidate earlier and reducing welfare relative to markets without a circuit breaker.

Our paper has important policy implications. Our data suggest circuit breakers alone may not be helpful in addressing financial market instability and indeed may generate perverse effects in poor information environments. On the other hand, combining mandated trading halts with policies aimed at improving information disclosure may prevent full market runs from occurring unnecessarily in illiquid markets. In addition, future research on the specific rules and features of circuit breakers would also be a productive agenda. Specifically, understanding the optimal trigger rules and length of a market halt could help design optimal circuit breaker policies. Our findings suggest that the length of a market halt should be given special attention. On one hand, longer market halts would provide more information accumulation and prevent market runs when the state is "good," but could also lead to extreme volatility, as highlighted in Figure 7, when the state is "bad." Finally, while in this paper we assume information is exogenous, one important way in which this framework can be extended is by letting investors decide how and when to obtain new signals. Studying the interaction between circuit breakers and the investors' incentives to acquire better information is an important avenue for future research.

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Appendix A Deriving the price schedule

As in Bernardo and Welch (2004), we assume that there is a risk-averse, competitive market maker who absorbs shares upon demand. Now we assume that the asset pays a random cash flow, z with mean v. Note that the investors are assumed to be risk-neutral, so they care only about v.

The market maker is immune to liquidity shocks and does not discount future consumption. In setting a price for buying 1 unit of the asset, the market maker behaves myopically, i.e. does not account for future trading opportunities. Let w_0 be the initial wealth of the market maker and w_k be the wealth after buying k units of the asset:

$$w_k = w_0 - \sum_{h=0}^{k-1} p_h + kz \tag{8}$$

The price is set in such a way that:

$$E[u(w_k)] = E[u(w_{k+1})] \tag{9}$$

where u is the utility function of the market maker. With the following assumptions:

$$u(w) = -e^{-\gamma w} \tag{10}$$

$$z \sim N(v, \sigma^2) \tag{11}$$

it is easy to show that the price is given by:

$$p_k = v - \frac{1}{2}\gamma\sigma^2 - \gamma\sigma^2 k \tag{12}$$

This is the same function used in the CARA-Normal example of Bernardo and Welch (2004) and it motivates the use of a linear price schedule in our experiment.

Appendix B Additional Empirical Results

Belief at First Sale	Coeff.	Std. Err.	P-Value
CB	0.000	0.020	0.989
LOW	-0.125	0.015	0.000
CBxLOW	-0.022	0.021	0.915
Cons.	0.643	0.015	0.000

Table 5: *Reports regression results from specification* (3) *using "bad" rounds only. The regression includes round fixed effects. There are 433 observations and the regression has an* $R^2 = 0.1973$. *Robust standard errors are reported.*

Probability at First Sale	Coeff.	Std. Err.	P-Value
CB	0.010	0.025	0.701
LOW	-0.078	0.019	0.000
CBxLOW	-0.024	0.026	0.352
Cons.	0.611	0.018	0.000

Table 6: *Reports regression results from specification* (3) *using 2nd half rounds only. There are 329 observations and the regression has an* $R^2 = 0.0803$. *Robust standard errors are reported.*

Time (Seconds)	Coeff.	Std. Err.	P-Value
CB	-0.559	1.082	0.606
LOW	21.430	6.011	0.000
CBxLOW	-2.917	1.398	0.107
Cons.	7.280	1.054	0.001

Table 7: *Reports regression results from specification* (4) *using "bad" rounds only. The regression includes round fixed effects. The regression includes round fixed effects. There are 376 observations and the regression has an* $R^2 = 0.319$. *Robust standard errors are reported.*

Time (Seconds)	Coeff.	Std. Err.	P-Value
CB	-1.048	1.119	0.350
LOW	1.790	2.159	0.408
CBxLOW	-1.430	1.963	0.467
Cons.	5.688	1.436	0.000

Table 8: *Reports regression results from specification* (4) *using 2nd half rounds only. The regression includes round fixed effects. There are 329 observations and the regression has an* $R^2 = 0.291$*. Robust standard errors are reported.*

Efficiency	Coeff.	Std. Err.	P-Value
CB	0.069	0.022	0.002
LOW	0.272	0.038	0.000
CBxLOW	-0.094	0.026	0.000
Cons.	0.725	0.034	0.000

Table 9: *Reports regression results from specification* (7) *using only the 2nd half rounds. The regression includes round fixed effects. There are 280 observations and the regression has an* $R^2 = 0.479$ *Robust standard errors are reported.*

Appendix C Experiment Instructions

This section reproduces instructions given to experiment subjects for the baseline CB sessions.

Instructions

You are about to participate in an experiment in the economics of decision-making. The National Science Foundation and other agencies have provided the funding for this project. If you follow these instructions carefully and make good decisions, you can earn a CONSIDERABLE AMOUNT OF MONEY, which will be PAID TO YOU IN CASH at the end of the experiment.

Your computer screen will display useful information. Remember that the information on your computer screen is PRIVATE. To insure best results for yourself and accurate data for the experimenters, please DO NOT COMMUNICATE with the other participants at any point during the experiment. If you have any questions, or need assistance of any kind, raise your hand and one of the experimenters will come.

Rounds

The experiment will be divided into 55 rounds. **The length of a round will be random** – you will never know how long a round will last or when it is about to end (details below). When a round ends, your experiment will show a round summary page in red for a few seconds and then a new round will begin. Decisions and points made in one round do not affect other rounds.

The Basic Idea

You and three other players are traders market where an asset is traded. Each round you start the game with one unit of a asset. **Your only decision is when, if ever, to sell your asset**. First, we will describe what happens if you decide to sell the asset before the end of the round and then we will describe what happens if you decide to keep the asset until the end of the round.

Selling

At any moment you can decide to sell the asset. **If you sell the asset, the asset is bought by the computer and you are paid a price**. The amount you will be paid depends only on how many other participants have already sold their asset: each sale of a asset lowers its price. The exact **price schedule** the computer will use is reproduced in Table 10. For example: if you decide to sell and you are the first to sell you will be paid a price of \$8 ; if 1 unit has already been sold (by the another participant) and you decide to sell now, you will be paid a price of \$6, etc.

Price schedule	
Number of assets already sold	Price you are paid if you sell
0	8
1	6
2	4
3	2

Table 10: Price Schedule

Holding on to the asset

What if you have decided not to sell your asset and the round randomly ends? One of the following will occur:

1. **Forced Sale:** You are forced to sell your asset, together with all the other players who are still in possession of their assets. Your points in this round are given by the price at which your asset is sold (see more below). **or**

2. **Payout:** You and all the other player(s) who decided not to sell receive the **asset payout, equal to 20 points**.

The computer will randomly decide whether the round ends in a Forced Sale or Fixed Payout. Each round has a 50% probability of ending with a Forced Sale and 50% probability of ending with the Fixed Payout.

Figure 1 illustrates what can happen at the end of a round and how this affects your score if you have not sold your asset by then.

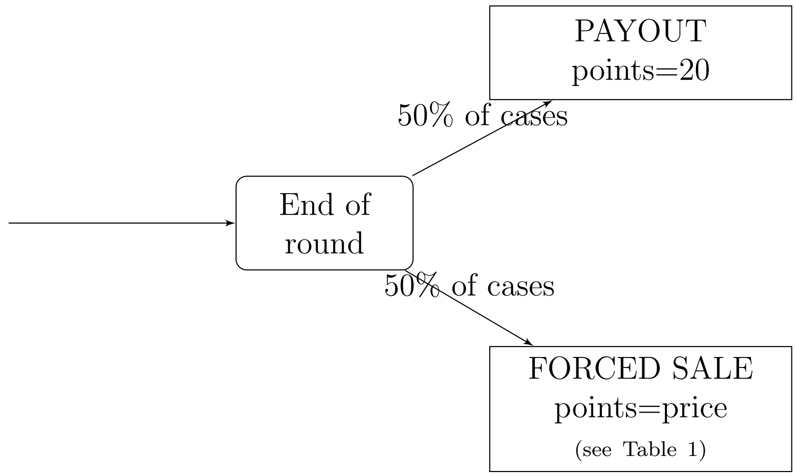

Figure 8: Points if you have not sold before the random end

Forced sales

When the round ends in a forced sale the computer will randomly decide the selling order for those players who have not sold earlier and pay each player in that order according to the schedule in Table 10. Examples:

- If none of the participants have decided to sell in the round and the round ends in a forced sale, the computer will randomly decide the selling order of the four participants. The first player will receive 8 points, the second 6 points, the third 4 points and the fourth 2 point.

- If two players decided to sell earlier in the round and the round ends in a forced sale the computer will randomly order the remaining 2 participants. The first participant will receive 4 points and the second 2 point.

The likelihood that the asset pays out

Whether a forced sale will occur in a particular round will not be known to you until it happens. However, **you will receive real-time signals about whether a Forced Sale**

will occur.

During the round you will receive either a **Good** or **Bad** signal every 4 seconds. On your computer screen you will be shown whether the current message is Good or Bad and a tally of the Good and Bad signals received so far in that round. For example, if a good signal arrives you may see **+Good (+2/-3)**. This message indicates that the current signal is Good and that there have been 2 Good signals and 3 Bad signals so far in the round.

This tally of signals will be updated every 4 seconds, until the round ends. In each round the signal tally will begin at **(+0/-0)**. Over time the Bad tally will become larger than the Good tally if a Forced Sale will occur. Conversely, over time the Good tally will become larger than the Bad tally if a Payout will occur.

Here are some details on the probability that a Good signal or a Bad signal arrives at each update. If in this round a Forced Sale will occur, then the probability that a Bad signal arrives is 67.5% and the probability that a Good signal arrives is 32.5%. If in this round the assets will Payout, then the probability that a Bad signal arrives is 32.5% and the probability that a Good signal arrives is 67.5%. Therefore at each update, a Bad signal is more likely to arrive if a Forced Sale will occur at the end of the round and a Good signal is more likely to arrive if a Payout will occur at the end of the round.

Market Freeze

During each round the market may freeze. During a market freeze your sell button will be disabled and you will be unable to sell your asset. The market will freeze when too many players attempt to sell their assets at once. Specifically, if one player sells their asset and another player attempts to sell their asset within 3 seconds of that sale the market will freeze. In this case the first sale will go through but the second will not. The market will unfreeze after 10 seconds at which point any participant who still owns an asset is again able to sell it if they choose to. The market can only freeze once per round. You will be notified when the market is frozen in the Market Status part of your screen.

Screen Information

The screenshot reproduced in Figure 9 shows an example of the screen you will see during each round.

The table at the top of the screen shows you the current signal and the tally of Good and Bad signals. You will see the signals and tallies updating during the experiment.

The plot shows you the current price that you can obtain if you sell your asset now, as a yellow line (remember this is entirely determined by how many people have already sold). The rightmost tip (the leading edge) of the line shows what is happening right now. Whenever some player sells his or her asset you will see a discrete jump in this line.

At any moment you can sell your asset by clicking the button at the bottom of the screen that says `Sell`. However remember that your sale goes through, the button will be disabled for the rest of the round.

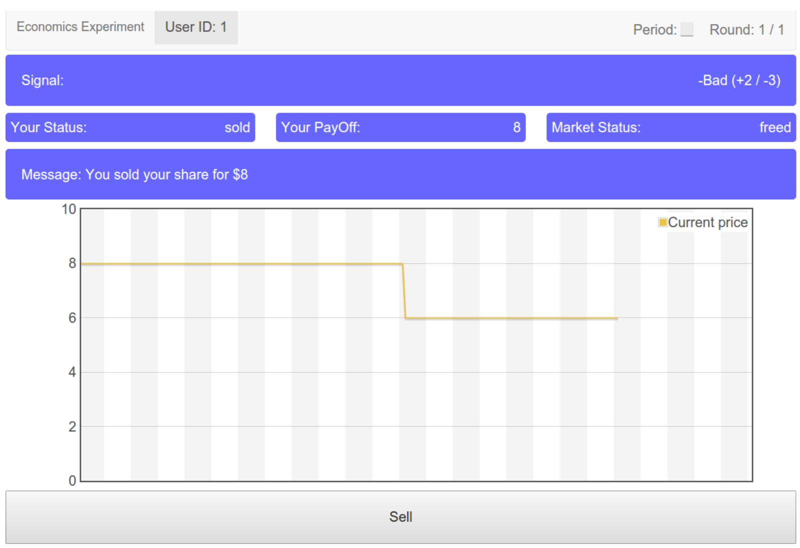

Figure 9: Example Screen View

Feedback

After the round is over, you will be shown a summary message in your page repeating your score and whether a forced sale occurred. The break between rounds will last around 10 seconds. During this break you will see: 1) your score in this round, 2) whether you sold your asset by clicking on the button during the round, 3) how the round ended: Forced Sale or Payout.

Earnings

At the end of the last round, you will be paid $7.00, plus earnings based on your total points throughout the experiment.

At the end of the experiment you will be presented with a summary table with your earnings in each round and your total earnings in the experiment. The points you earn in the experiment will be converted to U.S. Dollars at an exchange rate of 55 to 1. **THAT IS, FOR EACH 55 POINTS YOU EARN IN THE EXPERIMENT YOU WILL BE PAID 1 Dollar.**

Details

Here are a few more details on the experiment, in case you want to know.

How long will a round last?

- The minimum round length is eight seconds.
- The actual round length is random. The round ends with some constant probability every four seconds.
- The average length of a round is 32 second. Many rounds will last less than the average, and a few will last much longer.
- Rounds longer than a couple of minutes are so unlikely that you probably will never see one.

Frequently Asked Questions

Q1. Is this some kind of psychology experiment with an agenda you haven't told us?

Answer: No. It is an economics experiment. If we do anything deceptive, or don't pay you cash as described, then you can complain to the campus Human Subjects Committee and we will be in serious trouble. These instructions are meant to clarify how you earn money, and our interest is in seeing how people make market decisions.

Experiment Quiz

1. If you are the first person to sell, how many points do you earn in this round? ______
If you are the third person to sell, how many points do you earn in this round? ______

2. In a certain period, you did not sell your asset. How much do you earn in a Payout?
____
If, instead, you decided to sell and you're first to sell before the round ends, what would you have earned in this round? ______

3. If a round will end in a Forced Sale, what is the probability that a Bad signal arrives at each update? ________
If a round will end in a Payout, what is the probability that a Good signal arrives at each update? ________