Posted Offer Markets in Near Continuous Time: An Experimental Investigation

Douglas D. Davis

and

Oleg Korenok*

RRH: DAVIS & KORENOK: NEAR-CONTINUOUS POSTED OFFER MARKETS

Douglas Davis: Professor, Virginia Commonwealth University, Richmond VA 23284-4000.
Phone 1-804-828-7140, Fax 1-804-828-1719, E-mail dddavis@vcu.edu
Abstract

This paper reports an experiment conducted to evaluate a ‘near continuous’ variant of the posted offer trading institution, where the number of periods in a market session is increased by reducing sharply each period’s maximum length. Experimental results suggest that although decisions in time-truncated periods are not equivalent to periods of longer duration, extensive repetition improves considerably the drawing power of equilibrium predictions in some challenging environments. Nevertheless, significant deviations remain in the near continuous framework. We also observe that the extra data collected in the near continuous framework allows new insights into price convergence and price signaling.
I. INTRODUCTION

Posted offer markets occupy a central place in the laboratory investigation of market behavior. The posting of price decisions by sellers to consumers on a take-it-or-leave-it basis parallels important elements of naturally-occurring retail markets. The simultaneous-move feature of sellers’ price-posting decisions also parallels the structure of Bertrand-Edgeworth competition, a standard focus attention in industrial organization economics. In general, markets organized under posted offer rules converge robustly to competitive predictions. Indeed the general tendency of posted offer markets to generate competitive outcomes represents an instance of Smith’s (1982) “Hayek Hypothesis”, that private information regarding costs or values, along with the public messages of the markets (e.g., the posted prices) often suffice to generate competitive outcomes.

Nevertheless, in a number of circumstances, the organizing power of equilibrium predictions in posted offer markets is, at best, incomplete. For example, as Davis and Holt (1993) and Walker and Williams (1993) report, posted offer monopolists, tend to incompletely extract the available profits. Experiments by Davis, Harrison and Williams (1993) and Davis and Holt (1997) further indicate that sellers in standard implementations of the posted offer institution respond poorly (and in some instances abysmally) to demand shocks. Again, in a “swastika” design studied by Cason and Williams (1990), posted offer sellers respond asymmetrically to conditions of excess supply and excess demand. In such a design, sellers have a common unit cost and buyers have a common unit value. Relatively subtle alterations in the total number of units allocated to sellers relative to buyers causes the competitive equilibrium prediction to swing from the buyers’ values to sellers’ unit costs.
Under conditions of excess demand, sellers adjust fully to buyers’ values. However, given excess supply, prices drop incompletely toward unit costs.

In principle, these deviations from equilibrium outcomes may be quite important, as they suggest that institutional features of posted offer pricing may drive similar phenomena observed in some naturally-occurring contexts. The slow response of posted offer sellers to demand shocks, for example, represents the sort of friction that Neo-Keynesians use to motivate an upward sloping aggregate supply schedule. Similarly, the comparatively slow and incomplete downward adjustment of prices to conditions of excess supply in the swastika design is reminiscent of the “rockets and feathers” pricing patterns that characterize pricing in retail gasoline markets.

Many economists treat dismissively these potential policy implications. Despite the comparative simplicity of the laboratory markets, they argue, the limited number of decisions in a conventional laboratory session generates an experience profile insufficient to allow the emergence of equilibrium outcomes.1 Traditionally, experimentalists have attempted to increase experience profiles by inviting participants who participated once in a particular environment back for a second or even a third time to participate in “experienced” or “twice-experienced” markets.2 This approach has at least two shortcomings. First, participants experienced in this way do not necessarily get the right type of experience. The market (or game) starts anew with each new session, thus even experienced participants gain only limited insight into the decisions of others in their market. This sort of experience offers only limited insight, for example, into the capacity of sellers to coordinate activities by sending and responding to price signals. Second, and more important, generating extended
experience profiles in this way is quite expensive, both in terms of subject payment fees, and in terms of time spent by an investigator in the laboratory.

This paper introduces an alternative tool for increasing participant experience profiles in the posted offer institution. The basic idea is disarmingly simple. Rather than allowing sellers to proceed at their own paces, we truncate sharply the duration of decision periods so that more decision periods can fit into a single session. Increasing decision-profiles in this way is not without some parallels to natural contexts, particularly when making comparisons across trading institutions. Economists, for example, often evaluate posted offer market performance in light of markets organized under double auction trading rules. But high value items, such as stocks and other financial instruments typically trade in double auction markets. In contrast, exchange in posted offer markets is often characterized by the exchange of relatively low value consumer goods. In order to match the dollar volume associated with a single representative double auction transaction, sellers of many consumer goods may have multiple opportunities to revisit their pricing decisions.

The idea of increasing the number of periods in repeated simultaneous-move games to better evaluate equilibrium predictions is not entirely novel. Alger (1987) reports an experiment showing that extensive repetition in a posted offer market can generate considerably more cooperation than has been traditionally observed in markets of shorter duration. Some of Alger’s markets lasted more than 140 periods. Notably, however, the excessive temporal duration of some of the sessions reported by Alger provoked concern regarding the motivation for participant decisions. Other investigators have attempted to increase experience profiles by using either continuous, or extremely condensed decision periods. In particular, Deck and Wilson (2002, 2003 and 2007) use such techniques to
evaluate policy issues pertinent to e-commerce and retail gasoline pricing. Also, Millner, Pratt and Reilly (1990) study a “flow” market, where buyers and sellers trade streams of goods that are both produced and consumed continuously. None of these studies, however, explicitly considers the extent to which reducing the period length affects the performance of markets organized under posted offer trading rules.

To evaluate the effect of extensive repetition on posted offer market performance, we study the three contexts mentioned above, where equilibrium predictions have emerged incompletely in previous investigations: (a) a monopoly pricing exercise, (b) a “trend demand” design, where a series of demand shocks results first in an inflationary and then in a deflationary pattern of equilibrium price adjustments, and (c) a swastika design, characterized by extreme earnings inequities. In overview, experimental results indicate that while price adjustments in single time-truncated ‘short’ periods are somewhat slower than in standard ‘long’ trading periods, equilibrium predictions emerge more completely in the near continuous framework than in the standard laboratory posted offer market implementation. Nevertheless, in some important respects, convergence remains incomplete. Further, we find that extensive repetition allows insights into price adjustment dynamics that could not be observed in markets of shorter duration. In particular, sellers adjust more slowly to inflationary demand shocks than to comparable deflationary demand shocks. Sellers also respond more quickly and completely to conditions of excess demand than to conditions of excess supply.

We organize this paper as follows. Section II below introduces the near continuous posted offer framework, and presents the experimental design. Section III presents results. We offer some parting comments in a short fourth section.
II. THE NEAR CONTINUOUS FRAMEWORK AND THE EXPERIMENT DESIGN

A Near Continuous Posted Offer Market

For the most part, trading in our near continuous implementation of the posted offer institution follows standard posted offer procedures. At the outset of each period, sellers, endowed with unit costs, simultaneously make pricing decisions. Once all price posting decisions are complete, a public display of prices appears, and a simulated buyer makes purchases. The period concludes by showing each seller his or her own period sales and earnings. Figure 1 shows the screen display seen by a seller S1 in a computerized implementation of a posted offer market, as this seller decides on a price in period 4. As we can see, in period 3 seller S1 sold four units at a price of $2.10 per unit, and earned $2.00. Sellers S2, S3 and S4 posted prices of $1.80, $1.60 and $2.00, respectively. In period 4 seller S1 may offer up to six units for sale, with unit costs ranging from a low of $1.30 for the first unit to a high of $2.70 for the sixth unit.

Our near continuous institution differs from the standard posted offer implementation in that we supplement the tabular display of prices shown at the top of the panel, with a graphical representation of price postings for the period (shaded bars) and the preceding period (light bars). Own profits for the most recently completed period and for the preceding period are displayed similarly, as shown in the right side of the panel. We also streamline seller price posting procedures. Unlike the standard posted offer implementation, where sellers make and confirm both price and quantity choices, sellers here may complete posting decisions simply by typing an entry in the price box, and pressing ENTER. The program automatically inputs the maximum number of units that a seller may profitably offer at the
selected price (although sellers may override this entry if they like). Finally, to further speed decisions, we remove the standard price confirmation check.

This near continuous posted offer mechanism usefully allows for the collection of a very large amount of data in a standard laboratory session. Our debriefing of participants after a pilot session indicated that, at least with some mechanism experience, participants felt comfortable inputting decisions and responding to results in trading periods that lasted only seven seconds, a small fraction of the length of trading periods in many standard posted offer implementations.7

Experiment Design

Figures 2, 3 and 4 illustrate variants of the monopoly pricing problem, the trend demand design and the swastika design used here. In the monopoly pricing problem, shown in Figure 2, discrete demand steps make the price searching problem non-trivial, because these demand steps create spikes in the profit polygon.8 Notice in the right panel of the figure, that the monopolist can earn $7.20 by posting a price of $3.20. However, local profit maxima that extract a reasonably large portion of monopoly profits arise at prices of $2.70 and $3.70. From either of these nodes, even relatively large price deviations result in profit reductions relative to the local maximum.

Participant performance in a monopoly price exercise provides a useful baseline for evaluating the effects of extensive repetition on individual decisions. The extensive repetition allowed by the near continuous framework allows price-searching monopolists to develop a much richer experience profile. As a consequence, we anticipate outcomes to be closer to the optimal price and profit values. We evaluate the effects of the near continuous framework on monopoly pricing decisions with the following hypotheses.
Hypothesis 1a (Weak Convergence). Monopolists set prices closer to the optimal price and hence are able to extract more monopoly profits in the near continuous posted offer institution than in the traditional posted offer implementation.

Hypothesis 1b (Strong Convergence). In the near continuous posted offer institution, monopolists collapse on the global profit-maximizing price and extract fully all possible profits.

We offer these hypotheses to frame the subsequent analysis. Although extensive repetition may quite reasonably be expected to improve behavioral conformance with equilibrium predictions, it is not obvious a priori that extensive repetition will uniformly cause prices to converge with near zero variance on the global maximum.

Figure 3 illustrates a trend demand design. Here, four sellers are repeatedly endowed with unit costs that aggregate to generate the step-wise linear upward-sloping market supply schedule labeled “S.” For periods 1 and 2, the demand curve decays in 5 cent steps from an intercept of $2.70, as labeled by demand schedule D_{1,2}. In these periods, the equilibrium price and quantity predictions are $2.50 and five units, respectively. For each of the six periods following period 2, market demand shifts upward by 50¢, causing the equilibrium price to increase each period by 40¢ and the quantity to increase by two units. Equilibrium price and quantity predictions peak at $4.90 and 17 units in period 8. After repeating the market demand for period 8 in period 9, a deflationary cycle begins, with the demand curve shifting downward in 50¢ increments after each period 9 to 14 until demand returns to initial level, in period 15.
In Davis, Harrison and Williams (1993) and Davis and Holt (1997) sellers responded abysmally to these repeated demand side shocks. In the inflationary periods, prices drifted up slowly as sellers failed to appreciate the magnitude of the upward adjustment in the underlying equilibrium. Prices continued their upward drift well into the deflationary regime, until the underlying equilibrium fell below market prices. Then trading volume either tapered off or dried up completely as the surprised sellers missed the market. Here we study the extent to which repeated price posting opportunities at each demand step facilitate equilibrium price adjustments and efficiency extraction rates. Parallel to the monopoly pricing exercise, we evaluate the effects of rapid repetition with strong and weak versions of convergence.

**Hypothesis 2a (Weak Convergence).** Static equilibrium price and efficiency predictions emerge more fully in the near continuous posted offer institution than in the traditional posted offer implementation.

**Hypothesis 2b (Strong Convergence).** In the near continuous posted offer institution, markets respond completely to demand shocks.

Given that our near continuous variant imposes stationary repetition at each demand step, *ex ante* we would be very surprised if the near continuous variant did not facilitate a more complete equilibrium adjustment in the trend demand design. The more interesting issues here regard the extent to which rapid repetition improves the drawing power of competitive predictions, as well as the price adjustment process.

The swastika design, shown in Figure 4, allows insight into seller responses to conditions of extreme earnings inequities. In this design a total of 11 units costing $1.00 each are distributed as evenly as possible among four sellers, while a single (simulated)
buyer is endowed with reservation values for 16 units at $3.00 each. The combination of 16 units demanded and 11 units supplied creates an excess demand of five units. As highlighted by $P_1$ in the upper right corner of the figure, standard competitive price theory predicts that prices will rise to the buyers’ unit values of $3.00, and in this equilibrium all of the surplus will go to sellers. In a second regime, the number of units given to the buyer falls by five units to 11, and aggregate supply is increased to 16 units, by increasing each sellers’ allocation by one or two units. This relatively subtle set of changes converts the previous the excess demand condition to one of excess supply, and the equilibrium price prediction shifts down to the sellers’ $1 unit cost, indicated by $P_2$. In this new equilibrium all the trading surplus goes to the buyer side of the market.

Cason and Williams (1990) compare the results of posted offer markets conducted in this “swastika” design with some double auction markets conducted in the same design reported previously by Smith and Williams (1990). In stark contrast to the double auctions, the posted offer markets adjusted relatively slowly to the changes in the underlying equilibrium. More prominently, market responses were asymmetric. Sellers responded much more completely to conditions of excess demand than to conditions of excess supply. Here we investigate the extent to which extensive repetition fosters the emergence of the equilibrium price predictions, particularly in the excess supply condition. Specifically, we explore the following hypotheses.

Hypothesis 3a (Weak Convergence). In the swastika design static equilibrium predictions emerge more fully in the near continuous posted offer institution than in the standard posted offer implementation.
Hypothesis 3b (Strong Convergence). In the near continuous posted offer institution prices converge fully on equilibrium predictions in the swastika design.

The Matrix of Treatments and Experimental Procedures

Variants of Figures 2, 3 and 4, have been previously investigated in laboratory markets of relatively short duration, ranging from between 10 and 25 trading periods. In a 70 minute lab time-slot (exclusive of time spent reading instructions, re-initializing software and paying participants) we could conduct up to 60 seventy-second periods (or 600 seven second periods), easily enough time to explore decisions in all three designs in a single session.9

Thus, each session consists of a series of three sequences. Below we describe the structure of each sequence, and then we explain the order of sequences across sessions.

The Structure of Sequences. Our principle treatment is the use of traditional or near continuous implementations of the posted offer institution, so for each market sequence conducted in a “FAS” design with a relatively large number of seven second trading periods, we conduct an equal number of “SLO” market sequences, which consist of exactly one tenth the number of 70 second periods.10 To maintain the saliency of incentives across treatments, we adjust compensation levels per period by a factor of ten in each implementation. Table 1 summarizes the period structure and compensation rate for each sequence.

The Order of Sequences. The monopoly pricing exercise is a useful way to introduce the posted offer trading institution, and the individual decisions made in the monopoly sequences cannot generate group effects. For these reasons, we uniformly place the monopoly sequences first in each treatment. On the other hand, order of presentation effects may affect outcomes in the market sequences. We control for these potential effects by blocking the market sequences. Thus, the experiment uses an A-BC, A-CB design. We further mitigate
potential sequence-specific effects by anonymously regrouping participants at the beginning of each market sequence. 11

Table 2 summarizes the matrix of treatments. In total the experiment consists of eight 8-participant sessions. 12 As indicated by the columns in the right side of Table 2, we generate eight strictly independent FAS and SLO observations in both the trend demand and swastika designs. The eight sessions also generate a total of 32 observations in the monopoly MSLO and MFAS treatments. We supplement these observations with four MSLO observations that were collected in an otherwise unusable pilot session, and with nine MFAS observations conducted as the opening sequence of an unrelated experiment. Thus, in total, we have 36 MSLO and 41 MFAS observations.

**Procedures.** At the beginning of each session a monitor randomly seats eight volunteers at visually isolated computer terminals, and then reads aloud a set of typed instructions as participants followed along on a copy of their own. After responding to all questions, the monitor starts a monopoly pricing exercise (either SLO or FAS) as the first sequence. Participants in the MSLO sessions were given a pencil and paper, and were encouraged to use the full amount of time available in each decision period.

Upon completion of the monopoly pricing sequence, the monitor anonymously groups participants into two quadropolies and a second sequence begins, either in the trend demand, or in the swastika design. The monitor again anonymously regroups participants prior to a third sequence, which is conducted in the swastika or trend demand design that had not yet been conducted. At the end of the session, which lasts between 90 minutes and two hours, participants are privately paid the sum of their earnings for each of the three sequences plus a $6 appearance fee, and dismissed.
Participants were 64 student volunteers recruited from upper-level business and
graduate courses at Virginia Commonwealth University in the spring semester of 2005. Each
student participated in exactly one three-sequence session. Earnings (inclusive of the $6
appearance fee) ranged from $14.25 to $30.50 and averaged about $21.13

III EXPERIMENTAL RESULTS

Monopoly Pricing.

The left and right panels of Figure 5 illustrate frequency with which both the optimal
price $P_m = 3.20$ and the near optimal nodes $P_h = 3.70$ and $P_l = 2.70$ were selected in the
MSLO and the MFAS decision sequences. Inspection of Figure 5 makes obvious two results
of the monopoly pricing exercise. First, in the MFAS treatment the frequency of optimal and
near optimal price choices is much higher than in the MSLO treatment. Second, and
nevertheless, prices in the MFAS treatment fail to collapse on $P_m$, or even on $P_m$, $P_l$ and $P_h$
combined. For example, at the end of the MFAS treatment, only 32% of choices are at $P_m$,
and only 50% are at $P_m$, $P_l$ and $P_h$ combined. Thus, while the extensive repetition appears to
improve learning, learning remains incomplete.14

The information summarized in Table 3 allows a more formal evaluation of
hypotheses (1a) and (1b). Columns (2) to (4) of Table 3 evaluate the frequency of optimal or
near-optimal price choices in the MFAS and MSLO treatments. Each column lists the
combined frequency of $P_m$, $P_l$, and $P_h$ price choices in a period or period block.15 Monopoly
effective index 'M' values for the MFAS and MSLO treatments, printed in columns (5) to (7)
of Table 3 convey information regarding supra-competitive profit extraction rates across
treatments.16 Each entry in columns (5) and (7) reports the percentage of participants who
extracted at least one-half of the available supra-competitive profits in each period or period block.

Consider first performance in the MSLO treatment. As seen in column (2) and (5) results of our MSLO treatment parallel results previously reported, for example by Davis and Holt (1993) and Walker and Williams (1993). Here, even by the ninth and tenth periods, fewer than 20% of sellers chose $P_m \leq P_1 \leq P_h$, and only slightly more than half the sellers (53%) extracted at least half of the available supra-competitive profits.

To assess relative performance across the FAS and SLO treatments, two bases of comparison are pertinent. First, we compare performance on a unit of time basis. Given that we adjusted the time per period and incentives per decision by offsetting factors of ten, comparing decisions in 10 FAS periods with single SLO periods provides some sense of the extent to which rapid repetition affects the drawing power of equilibrium predictions in a given timeframe. Columns (3) and (6), which list, respectively, optimal price frequencies and monopoly profit extraction rates for each ten period ‘block’ in the MFAS treatment, presents data that allows this comparison. Second, we compare performance on a per period basis. This comparison allows insight into the extent to which single FAS decisions correspond to single SLO decisions. Columns (4) and (7), which present price choice and monopoly profit extraction data for the first ten periods of the MFAS treatment, allow this second comparison.

Consider first unit of time comparisons. Examining columns (2) and (3) observe that for each period block after the first, significantly more sellers selected optimal or near optimal prices in the MFAS treatment than in the MSLO treatment (using a Fisher Exact Probability ‘FEP’ test). Similarly, comparing the incidence of $M_{\geq .5}$ in columns (5) and
notice that a significantly higher percentage of sellers extracted at least half of the supra-competitive profits in the MFAS treatment than in the MSLO treatment in 7 of 10 periods (FEP, $p<.10$). These price convergence and profit extraction results combine to form our first finding.

**Finding 1a(i):** On a unit of time basis, the near continuous framework facilitates identification of optimal or near optimal price choices. Sellers in the MFAS treatment tend to price nearer to the monopoly optimum and tend to extract a higher percentage of available profits than do sellers in the MSLO treatment.

Consider next period comparisons. Examining optimal and near optimal price choices entries for the first 10 MFAS periods in column (4) in light of comparable information for the MSLO periods, in column (2) reveals that fewer near-optimal price choices were selected in the each initial MFAS period than in the corresponding MSLO period (although the difference was significant only in periods nine and ten). Comparison of profit extraction rates for the first ten MFAS periods, shown in column (7), with the ten MSLO periods in column (5), reveals even more sizable differences. Monopoly extraction rates are lower in each of the first ten MFAS periods than in the MSLO counterpart, and significantly so in nine of the ten instances. This is a second finding.

**Finding 1a(ii):** On a per decision basis initial MFAS decisions deviate further from optimal choices than single MSLO decisions. Sellers in the first ten periods of the MFAS treatment extract a lower percentage of available profits than do sellers in the ten periods of MSLO treatment.
Given that all sessions started with the monopoly sequences, this finding is not terribly surprising. As might be expected, participants need some time to accustom themselves to the rapid pace of decisions in the MFAS treatment. However, the number of initial decision periods participants needed to become comfortable with the near continuous mechanism merits some comment. In the first five periods of the MFAS treatment, 62% of all price postings were zeros, indicating that the majority of sellers had not yet figured out how to enter prices. In the MSLO treatment, only 8% of sellers failed to make a first period pricing choice.

A final observation regards overall performance in the MFAS treatment. Despite the improvement in rates of optimizing behavior in the MFAS treatment, observe that prices and earnings do not converge completely on the optimum in the MFAS condition, even in the final ten periods of a 100 period sequence. For example in the bottom row of Table 3, notice in column (3) that only 50% of price choices are optimal or near optimal, and in column (5) that only 71% of the MFAS sellers extract more than half of the available supra-competitive profits. The extent to which choices deviate from the optimum merits some emphasis. Clearly, the monopoly design studied here presents a non-trivial problem for participants. But our results suggest real limits on the amount of learning that may be expected in an individual decision-making pricing context. This is our third finding.

**Finding 1b:** Prices do not collapse on optimal choices in the MFAS treatment. In the near continuous framework the discovery of optimal and near optimal prices remains incomplete.

**The Trend Demand Design**
Figure 6 illustrates mean transaction price paths for the eight TDSLO and eight TDFAS sessions. To facilitate across treatment comparisons price points for the TDFAS sessions, shown in the right panel of Figure 6, are ten-period means. As inspection of the figure makes clear, on a unit of time basis, the near continuous framework substantially improves price-tracking performance in the trend demand design. In the TDSLO sessions, shown in the left panel of the figure, price paths for individual markets vary widely, and as a rule, sellers miss the movement in the underlying equilibrium. This outcome parallels the earlier experimental results mentioned in the introduction. In contrast, in the TDFAS sessions, illustrated in the right panel, prices clearly adjust to the underlying inflationary, then deflationary equilibrium price path.

We evaluate formally hypotheses (2a) and (2b) with the price and efficiency information summarized in Table 4. In distinction to the monopoly pricing treatment we focus here only on per unit of time comparisons, because no natural basis for per period decisions exists in the trend demand design. Columns (2) and (3) present mean absolute deviations of transactions prices from the underlying equilibrium for single TDSLO periods (in column 2) or for 10 period ‘blocks’ in the TDFAS treatment. As comparison of the columns makes clear, in 14 of 15 instances absolute price deviations in the TDFAS treatment are less than those in the TDSLO treatment, and, as the asterisks in column (3) suggest, the differences are significant in 13 of those cases using a Mann-Whitney test. Similarly as the efficiency information summarized in columns (4) and (5) illustrates, mean efficiency extraction rates in the TDFAS treatment both sizably and significantly exceed comparable rates for the TDSLO treatment in each of the 15 comparisons, again using a Mann-Whitney test. This yields a fourth finding.
**Finding 2a:** On a per period of time basis, the near continuous framework improves the organizing power of equilibrium predictions in the trend demand design. The absolute value of price deviations tend to be smaller and efficiency extraction rates are uniformly higher in the TDFAS sessions than in the TDSLO sessions.

As we indicated previously, given that the TDFAS treatment induces stationary repetition at each demand step, we were not terribly surprised that these markets conformed more closely with underlying equilibrium conditions than the TDSLO markets. Indeed, we would have been surprised to see the opposite. More interesting are the substantial deviations from equilibrium predictions that persist in the TDFAS markets. Notice, for example, in column (3) of Table 4 that the mean absolute value of price deviations exceeds 25¢ in six of the fifteen TDFAS period blocks. Similarly, observe in column (5) of Table 4 that 90% or more of the gains from exchange are extracted in only four TDFAS period blocks. Indeed, in five period blocks no more than 70% of the available gains from exchange are extracted. These efficiency extraction rates remain low by the standards of, say, the double auction where virtually all gains from trade are extracted each period. This is a fifth finding.

**Finding 2b:** Despite the improved drawing power of equilibrium price and efficiency predictions for the TDFAS markets over the TDSLO markets, outcomes in the TDFAS treatment do not collapse on equilibrium predictions. Sizable deviations from equilibrium price and efficiency predictions persist in the TDFAS markets.
Further inspection of the price deviation and efficiency extraction rates for the TDFAS treatment, shown in columns (3) and (5) of Table 4, reveals an interesting asymmetry in seller responses to inflationary and deflationary shocks in the TDFAS environment. Following the inflationary shocks (italicized), mean absolute price deviations are never less than 27¢ and mean efficiencies never fall below 79% (and average 86%). In contrast, following the deflationary shocks (bolded), mean absolute price deviations never exceed 15¢ and mean efficiency never exceeds 74% (and average just 67%).

The median posted price and mean efficiency paths illustrated in Figure 7 provide some insight into this asymmetric outcome. Each panel of Figure 7 illustrates the path of price deviations or efficiencies for the ten periods following an inflationary or deflationary shock. Progressively heavier lines represent responses to later shocks. Consider first the inflationary shocks, shown in the left side of Figure 7. As seen in the upper panel, prices adjust slowly in a fairly smooth, almost linear manner. Deviations start near the equilibrium for the preceding shock (a deviation of -$0.40) and rise to the new equilibrium both slowly and incompletely. However, as evidenced by the corresponding efficiency paths shown in the lower left panel of Figure 7, the efficiency consequences of this sticky price adjustment process are minor. The sellers extract roughly 90% of the possible gains from exchange immediately following the shock, and do not, collectively, extract much more as the period block progresses.

On the other hand, sellers respond to deflationary shocks with considerably more speed. As shown in the upper right panel of Figure 7, median prices collapse to within 10¢ of the post-shock equilibrium by the sixth period. As suggested by the sharply upward sloping efficiency paths in the lower right panel of Figure 7, profit losses drive this price
adjustment process. Following a deflationary shock trading efficiencies (and by extension profits) fall off precipitously at pre-adjustment prices. Sellers can recover earnings only by reducing price. Thus, the differential effects of inflationary and deflationary shocks on earnings appear to explain sellers’ comparatively slow response to inflationary shocks. Following an inflationary shock, sellers receive only the subtle signal that the high pricing seller exhausts his or her offer quantity to indicate that they may raise prices. In contrast, following a deflationary shock all sellers receive a clear signal of lost profits.

We find intriguing the potential parallels of these asymmetric responses to demand side shocks to naturally occurring contexts. For example, results here suggest that prices in posted offer type markets respond to aggregate demand increases relatively slowly, damping inflationary pressures. On the other hand, the same markets respond much more quickly to unanticipated aggregate demand reductions. This ‘balloons and bricks’ response to demand shocks is just opposite to the ‘rockets and feathers’ response to cost shocks that has been the subject of considerable attention in retail gasoline pricing. Results observed here suggest the possibility that the dynamic response of markets to demand and supply shocks may be very distinct.

Prior to considering the effects of near continuous repetition in the swastika design, we comment briefly on the evidence of learning suggested by the price deviation paths shown in the upper panels of Figure 7. A collapse of the progressively darker median posted price deviation paths on zero would indicate that sellers learn to anticipate the repeated 40¢ shocks each ten periods. Curiously, despite the fact that sellers tend to discover the equilibrium following each shock, they do not appear to learn to anticipate these adjustments, either in the inflationary or in the deflationary regime. With a yet longer series, sellers may
learn to anticipate demand shocks. However, even with extensive repetition, sellers do not learn quickly the pattern of large persistent shocks.

The Swastika Design.

The swastika design differs from the trend demand design in that sellers are given a very extended amount of time to adjust to changes in underlying conditions. However, while sellers never possess any unilateral market power, in the case of excess supply the equilibrium is undesirable in the sense that the sellers earn nothing. The left and right panels of Figure 8 (formatted as Figure 6) illustrate mean transactions prices for the SWSLO and the SWFAS treatments, respectively. As in the preceding sections, illustrated price points in the SWFAS treatment are for ten period blocks. Looking first at results of the SWSLO sessions, shown in the left panel, observe that sellers respond asymmetrically to conditions of excess demand and excess supply. In the excess demand condition, in effect from periods one to nine, prices rise fairly uniformly toward the $3.00 unit value limit. However, in the excess supply regime, periods 10 to 18, prices fall very incompletely to the $1.00 unit cost limit. These outcomes parallel the results reported by Cason and Williams (1990).22

Turning to the SWFAS sessions, summarized in the right panel of Figure 8, notice that on a per unit of time basis, extensive repetition again appears to uniformly increase the organizing power of equilibrium predictions. In the initial excess demand condition, prices rise both more completely and more quickly to the $3.00 limit in the SWFAS treatment than in the SWSLO treatment. Mean transactions prices for the SWFAS markets also decay more completely toward unit costs in the excess supply regime than was observed in the SWSLO markets. Importantly, however, very considerable heterogeneity characterizes price outcomes in the excess supply segment of the SWFAS markets. In those sessions where
prices do eventually fall toward the $1.00 unit costs, the price adjustment process is slow relative to the price ascendance observed in the excess demand condition. But not all of the SWFAS markets converge. In two instances, transactions prices shoot up in the last 20 periods, after a long decay. In three remaining instances prices do not converge at all, and consistently remain closer to the $3.00 limit price than to unit costs.

The summary price information presented in Table 5 allows formal evaluation of hypotheses 3(a) and 3(b). A comparison of mean price deviations for the MSLO periods, listed in column (2), with comparable information for 10 period blocks, shown in column (3), clearly indicates that on a per unit of time basis, the near continuous framework improves the drawing power of underlying equilibrium predictions. For each of the first nine comparisons, deviations in the SWFAS treatment are considerably smaller than comparable deviations in SWSLO treatment. As indicated asterisks in column (3), these differences are uniformly significant using a Mann-Whitney test.

In the excess supply regime, starting in period block 10, observe that prices begin to decay slowly following the market adjustment in the SWFAS markets. Transaction price deviations in the SWFAS treatment actually exceed those in the SWSLO treatment in period blocks 10 and 11, and are not significantly smaller in period block 12. However, starting with period block 13 mean transaction price deviations for the SWFAS treatment fall significantly below comparable deviations for the SWSLO treatment, and are significantly smaller for each period block 14 to 17. This is a sixth finding.

**Finding 3(a):** Evaluated on a per unit of time basis, mean prices in the SWFAS treatment more nearly approach the underlying equilibrium prediction than comparable mean prices in the SWSLO treatment.
Although prices in the SWFAS design approach competitive predictions more completely than in the SWSLO treatment, we observe also that conformance with equilibrium predictions in the SWFAS treatment is both imperfect and asymmetric. In the initial excess demand regime, prices converge quickly to the upper limit. As shown in column (2) of Table 5, by the fourth period block mean prices are within eight cents of the competitive prediction. However, in the excess supply regime, prices fall only slowly. Mean transactions prices don’t fall more than halfway to unit costs until the fifth period block of the excess supply regime (period block 13), and are within 70¢ of the competitive prediction only once (in period block 16). Indeed, mean price deviations in the SWFAS design actually rise in the last three period blocks, climbing from 68¢ to 84¢ then to 110¢ in the final period block.

Reviewing again Figure 8, note that mean prices also disguise the very considerable heterogeneity of outcomes across the SWFAS markets. The incomplete drawing power of competitive predictions in the excess supply regime represents a seventh finding.

Finding 3(b): In the SWFAS sessions, convergence to the competitive prediction is essentially complete under conditions of excess demand. However, under conditions of excess supply convergence in the SWFAS sessions remains incomplete on average, even after 90 trading periods. In several markets, prices fail to converge at all.

The large and increasing deviations from competitive predictions observed during the excess supply phase of some sessions in the SWFAS treatment suggests that in some instances sellers may learn to collude tacitly quite effectively. We defer investigation of this
topic to future investigation, but observe that the extra repetition allowed by the near
continuous framework provides a promising context for investigating such behavior.

Consider now again the relationship between single FAS and single SLO decisions.
Unlike the monopoly design, participants in the swastika design uniformly had extensive
practice inputting prices and interpreting results. For this reason, comparing decisions in
individual SWFAS and SWSLO periods allows some additional insight into the effects of
period length truncation on price responsiveness. Columns (2) and (3) of Table 6 (formatted
as Table 5) show, respectively, mean transactions prices for the first nine SWSLO and for the
first nine SWFAS periods. Looking across columns observe that for each comparison
deviations are larger in the FAS period than in the comparable SLO period. Further, as the
asterisks in column (3) indicate, these differences are significant so in six of the nine
instances, using a Mann-Whitney test \(p<.10\). This comparison indicates that even with
mechanism experience, markets adjust less quickly to the underlying equilibrium in
individual FAS periods than in comparable SLO periods.

FAS markets, however, catch up rather quickly. Column (4) lists the mean price
deviations for every second FAS period (periods two, four, six, etc.) and column (5) lists the
mean price deviation for every third FAS period (periods three, six, nine, etc.) As the
absence of asterisks in column (4) suggests, using a two-period FAS ‘cycle’, mean price
deviations in the SLO design are no longer significantly smaller than in the FAS design.
Indeed, as indicated by the bolded entries, using a two-period cycle, deviations are smaller in
the FAS treatment in six of the nine comparisons. As shown in column (5), adjustment rates
improve yet more when comparing the SLO treatment to FAS cycles of three periods. Using
three-period cycles, FAS market deviations are smaller for each of the comparisons after the first, and significantly so in three instances.

We are reluctant to offer a specific number of FAS periods necessary to elicit price responses comparable to a single SLO period. A variety of factors, including participant experience levels, the number of other sellers in a market and the underlying design may affect this comparison. Further, we have no particular reason to believe that the rate of tradeoff is constant. However, evidence reported here suggests that once participants have some experience with the price setting process, convergence in FAS periods may be only slightly slower than in SLO periods. This is an eighth finding.

Finding 3(c): On a per period basis SWFAS markets, converge more slowly to the competitive prediction than do SWSLO markets. However, the SWFAS markets quickly catch up to and surpass the adjustment rates observed in the SWSLO markets.

IV. PARTING COMMENTS

Critics of laboratory market experiments can question the potential policy implications of posted offer type experiments because sellers gain too little experience with the underlying market environment for equilibrium predictions to emerge. The near continuous variant of the posted offer institution introduced in this paper represents a partial response to that criticism. The experimental results presented here suggest strongly that the extensive repetition allowed by the near continuous framework does indeed improve the drawing power of underlying equilibrium predictions. On a per unit of time basis, sellers in our FAS markets extract monopoly rents more quickly, and adapt to demand shocks and
equilibrium predictions that generate extreme earnings inequities are completely than do
sellers in our SLO markets.

Truncating the length of decision periods, however, is not without consequences. On
a per period basis FAS markets adjust less quickly than SLO markets, particularly at the
outset of sessions when participants are learning how to manipulate the price-setting
software. Even with mechanism experience a single FAS period is less than fully
comparable to a SLO period. Nevertheless, given mechanism experience, the difference
between FAS and SLO periods deteriorates. For this reason we feel reasonably confident
that we are able to collect effectively longer data series in a given time frame in near
continuous markets.

Of course, the near continuous framework allows no direct assessment of any
naturally-occurring phenomenon. In particular we make no claim about the relevance (or
irrelevance) of time restrictions in natural contexts. However, the near continuous
framework is useful for at least two purposes. First it can help with theory rejection. If, in a
future experiment in the near continuous framework, we observe persistent deviations from
competitive predictions, we can observe that these predictions fail in an institutional setup
that generates predicted or near-predicted equilibrium outcomes under very challenging
“boundary” circumstances.

Second, the effectively longer data series created with extensive repetition allow
additional insights into the performance of posted offer markets. In the trend demand design,
for example, market responses suggest an asymmetry in seller responses to inflationary and
deflationary demand shocks. In inflationary periods, prices adjust upward slowly but trading
efficiency remains high. In deflationary periods, prices adjust downward rather more
quickly, but only following huge efficiency losses. This ‘balloons and bricks’ response to demand shocks is just opposite to the ‘rockets and feathers’ response to supply shocks. Again, results from the excess supply phase of the swastika design suggest that the near continuous framework may provide a useful context for studying price signaling and tacit collusion.

An immense portion of trade in developed economies is conducted in markets with posted prices. Our understanding market performance in this institution remains importantly incomplete. The mechanism introduced in this paper allows improved insight into posted offer market dynamics that we intend to pursue in future research.
References


Kruse, J. “Nash Equilibrium and Buyer Rationing Rules: An Experimental Analysis,”  


FIGURE CAPTIONS

Figure 1. A Seller Screen Display in a Near Continuous Posted Offer Market.

Figure 2. A Monopoly Pricing Design.

Figure 3. A Trend Demand Design.

Figure 4. A Swastika Design.

Figure 5. Price Posting Frequencies at Optimal and Near-Optimal Nodes in the MSLO and MFAS Pricing Sequences.

Figure 6. Mean Transactions Prices for 8 TDSLO and 8 TDFAS sessions. Key: In the left panel, each line illustrates the mean transactions price for a single session. In the right panel each line illustrates mean transactions prices for 10 period blocks in a TDFAS session. Broken or incomplete series reflect periods in a session where no contracts occurred. In each panel, the heavy dashed line denotes the underlying equilibrium price each period.

Figure 7. Mean Transactions Price and Mean Efficiency for the 10 periods following each inflationary demand shock (left panels) and each deflationary demand shock (right panels) in the TDFAS sessions. Key: Progressively darker lines illustrate later price or efficiency paths

Figure 8. Mean Transactions prices in SWSLO and SWFAS Sessions.
A separate appendix, available upon request, contains detailed instructions for the experiments.

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Authors:

Davis: Professor, Virginia Commonwealth University, Richmond VA 23284-4000. Phone 1-804-828-7140, Fax 1-804-828-1719, E-mail dddavis@vcu.edu

Korenok: Assistant Professor, Virginia Commonwealth University, Richmond VA 23284-4000. Phone 1-804-828-3185 Fax 1-804-828-1719, E-mail okorenok@vcu.edu

1. Binmore (1999) implores experimentalists to give participants sufficient opportunities for learning when conducting experiments.

2. In a number of market environments, experimenters have also made efforts to use both more sophisticated participants, and participants with experience in the relevant natural circumstances. As Holt (1995, p. 353) observes, the use of such specialized participants typically does not importantly affect outcomes.

3. For example, Harrison, McKee and Rutstrom (1989, p. 89) comment “one of us observed of these experiments in progress, and was struck by the widespread boredom of the
subjects, as well as their relief at the end of the session.” The experiment reported in this article changes marginal financial incentives across treatments in order to keep total expected payouts constant. The idea of increasing the experience profile by reducing the period length proposed here is not without controversy, because such period-length reductions necessarily reduce the financial incentives associated with any particular decision. Holt (1995, p. 404), argues that “for most purposes, incentives should not be diluted to keep earnings constant when the number of market periods is increased.” Whether the dilution of incentives adversely affects decisions in the near continuous framework proposed here is an empirical question that will be resolved by laboratory testing.

4. In non-market contexts, Kurzban and Houser (2005), Kurzban, McCabe, Smith and Wilson (2001) and Murphy, Rapoport and Parco (2006, 2007) report experiments in “real time” environments designed to evaluate notions of trust, reciprocity and cooperation.

5. We term the posted offer variant studied here as “near continuous” because the institution retains the discrete simultaneous move structure explicitly implied in the static models of Bertrand-Edgeworth competition. Only Deck and Wilson (2002, 2007) approach the rapidly repeated simultaneous-move framework we propose here. The remaining experiments involve true real time (e.g. sequential move) contexts. Modeling decisions in a real-time environment requires an explicit dynamic analysis.

6. The automated buyer routine makes all profitable purchases of units offered by sellers, starting with the lowest priced units first. In the case of a price tie, the automated buyer rotates purchases as evenly as possible among the tied sellers. The use of an automated buyer routine is typical in posted offer market experiments. Except under specialized circumstanced, human buyers tend to similarly engage in full demand revealing
behavior. For example, in a “Buyer Market Power” design reported by Davis and Williams (1990), where the withholding of a single unit by either of two buyers shifts downward substantially the equilibrium price buyers never recognized their price-manipulating capacity, and consummated very nearly all profitable trades. Experimental results by Davis and Williams (1991) and Kruse (1993) suggest that sellers with market power price more tentatively when they are aware that humans rather than a computer makes purchase decisions. However, the only evidence that posted offer buyers actually attempt strategic counter-withholding activity arises in contexts like those reported by Ruffle (2000) and Davis and Wilson (2007), where buyers are very large relative to the market, and where they have full information about underlying supply and demand conditions. When sellers have no market power, and when buyers are presumed to be small relative to the market (as is the case studied here) the use of automated buyer appears to be relatively innocuous.

7. However, as we observe in the results, several time-truncated trading periods are necessary for participants to use fluidly this price-setting mechanism.

8. Davis and Harless (1996) study a variant of the design shown in Figure 2. Results of the Davis and Harless study are not directly comparable to present analysis, because the price grid was restricted to fairly coarse increments (of 5¢ or 25¢). However, the “lumpiness” of the profit polygon shown in Figure 2 is characteristic of many of the earlier studies. See, for example, the discussion in Davis and Holt (1993), ch. 4.

9. We note that a sizable number of laboratory posted offer markets consist of more than 10 to 25 trading periods. Markets of such short duration were typical in the 1980’s and early 1990’s, when the basic properties of posted offer markets were being explored. (The 100-period markets reported by Friedman and Hoggatt (1980) in their pioneering study of
noncooperative oligopoly are an interesting early exception.) Most (but not all) recent papers report markets that consist of between 40 and 60 trading periods, and a few studies, such as Durham et al. (2004) report some markets with as many as 80 periods. Our near continuous implementation may also be used to more examine more fully the phenomena that have been the subject of more recent investigation. The three designs evaluated here represent an initial baseline study conducted to assess the benefits of the near continuous framework.

10. Standard posted offer markets are typically self-paced, so no natural reference time exists for the “SLO” markets. Our experience with the average pace of posted offer markets with simulated buyer led us to choose the 70 second period length. In any case, 70 seconds is not an inordinately long maximum period length. Posted offer markets with real (non-simulated) buyers typically take several minutes to complete.

11. Note however, that our design does not fully block treatments, because the TDFAS and SWFAS treatments never follow an MSLO treatment, and TDSLO and SWSLO treatments never follow a MFAS treatment. We have no a priori reason to believe that such sequences would be a source of significant interaction effects (and indeed, we thought that following an initial MFAS or MSLO treatment with a comparably timed market design would facilitate understanding of market procedures). However, we acknowledge that our design does not control for such interactions.

12. In some sessions more than eight students met their appointment. In these sessions volunteers elected to take a $10 payment and returned for a session at a later time.

13. This excludes the 13 “other” monopoly participants in the monopoly pricing exercise. Earnings for the “other” participants parallel the mean and range reported in the text. Also, each “other” participant participated in exactly one of the sessions reported here.
14. The comparatively high incidence of choices at \( P_l \) and \( P_h \) in the MFAS periods suggests that MFAS sellers isolate on local optima to a higher extent than MSLO sellers. This may be driven, for example, by the use of a relatively finer price grid by MFAS sellers. However, we wish to emphasize that no evidence suggests that sellers in the MSLO treatment actually used the extra time and materials provided to attempt to calculate the underlying equilibrium. MSLO sellers rarely used the pencil and papers we provided. Indeed, absent information about underlying demand curve it is not obvious how they might make such a calculation.

15. We report combined \( P_m \), \( P_l \) and \( P_h \) choice frequencies in Table 3 to facilitate comparison with Figure 5. Comparing only \( P_m \) frequencies across treatments generates very similar statistical results. The only consequence of using \( P_m \) frequencies is that the difference between MFAS and MSLO treatments for period block 2 is no longer significant.

16. The monopoly efficiency index, first developed by Plott and Smith (1978) reports the percentage of supra-competitive profits extracted by the monopolist. Formally, in a given period \( i \), \( M = (\pi_i - \pi_c) / (\pi_M - \pi_c) \), where \( \pi_M \) denotes maximum available monopoly profits, and \( \pi_c \) denotes competitive profits and \( \pi_i \) denotes period \( i \) earnings.

17. For purposes of parsimony we evaluate hypotheses in this design, as well as in the other designs, with non-parametric tests. Parametric regression analyses yield results comparable to those reported here.

18. Comparing the first 15 TDFAS periods with the 15 TDSLO decisions biases results in favor of the TDFAS treatment because demand shifts only once in the first 15 TDFAS periods, rather than 12 times in the comparable TDSLO periods. Similarly, comparing the first period following each demand shift (e.g, TDFAS periods 1, 21, 31, 41,
etc. with TDSLO periods 1, 3, 4, 5, etc.) also biases results in the favor of the TDFAS treatment, since TDFAS participants benefit from any price adjustment toward the underlying equilibrium achieved in the preceding nine periods. We consider again single FAS and SLO decisions when assessing results for the swastika design, below.

19. For example, in a series of five double auctions in a trend demand design reported by Davis, Harrison and Williams (1993) efficiency extraction rates averaged 98%, and never fell below 93% in any period.

20. Notice that Figure 7 illustrates posted rather than transactions prices. Price postings better reflect learning than transactions prices, as the latter are truncated by being in the “strike” range. Also, we illustrate median rather than mean prices as mean price postings are inordinately affected by occasional outliers.

21. We are grateful to a referee for suggesting this terminology.

22. More specifically, these results parallel those posted offer sessions reported by Cason and Williams (1990) where the excess demand phase preceded an excess supply phase. Cason and Williams also report a pair a posted offer sessions where the excess supply phase appeared first in sequence. Prices in the excess supply phase of these sessions also decayed only slowly toward unit costs, but from a much lower initial level. Order of sequence effects doubtfully explain pricing outcomes observed in the excess supply phase of the SWFAS sessions, shown in the right panel of Figure 8. In a recent experiment Davis (2006) observes very similar pricing patterns in a series of stand-alone sessions that parallel in critical respects the excess supply phase of the SWFAS sessions.
23. Participants in the SWFAS treatments either had previously made decisions in 25 SLO periods (ten in the MSLO sequence and 15 in the TDSLO sequence), or in 100 FAS periods (in the MFAS sequence).
### TABLE 1.
The Structure of Sequences

<table>
<thead>
<tr>
<th>Design</th>
<th>Number of Periods</th>
<th>Maximum Period Length</th>
<th>Conversion Rate ($LAB to $US)</th>
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<td>Monopoly</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>MSLO</td>
<td>10</td>
<td>70 seconds</td>
<td>10:1</td>
</tr>
<tr>
<td>MFAS</td>
<td>100</td>
<td>7 seconds</td>
<td>100:1</td>
</tr>
<tr>
<td>Trend Demand</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>TDSLO</td>
<td>15</td>
<td>70 seconds</td>
<td>10:1</td>
</tr>
<tr>
<td>TDFAS</td>
<td>150</td>
<td>7 seconds</td>
<td>100:1</td>
</tr>
<tr>
<td>Swastika</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>SWSLO</td>
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<td>70 seconds</td>
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</tr>
<tr>
<td>SWFAS</td>
<td>180</td>
<td>7 seconds</td>
<td>100:1</td>
</tr>
<tr>
<td>Session</td>
<td>Sequence</td>
<td>Number of Observations</td>
<td></td>
</tr>
<tr>
<td>---------</td>
<td>----------</td>
<td>------------------------</td>
<td></td>
</tr>
<tr>
<td>1</td>
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<td></td>
</tr>
<tr>
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<td>SWFAS</td>
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</tr>
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<td>TDFAS</td>
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</tr>
<tr>
<td>5</td>
<td>MFAS</td>
<td>8</td>
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<td></td>
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<td></td>
<td>SWSLO</td>
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<td></td>
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<tr>
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<td>MFAS</td>
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<td></td>
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<td>TDSLO</td>
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</table>

Other: 4

Total: 36 41 8 8 8 8 8 8
### TABLE 3.

Monopoly Design, Price Convergence and Profit Extraction Rates.

<table>
<thead>
<tr>
<th>Period or Block</th>
<th>Sellers Posting $2.70, $3.20 or $3.70 (Frequency)</th>
<th>Sellers with M≥5 a (Frequency)</th>
</tr>
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<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
</tr>
<tr>
<td>Period or Block</td>
<td>MSLO (Periods)</td>
<td>MFAS (Ten Period Blocks)</td>
</tr>
<tr>
<td>1</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>2</td>
<td>3</td>
<td>4**</td>
</tr>
<tr>
<td>3</td>
<td>3</td>
<td>19**</td>
</tr>
<tr>
<td>4</td>
<td>0</td>
<td>30**</td>
</tr>
<tr>
<td>5</td>
<td>6</td>
<td>32**</td>
</tr>
<tr>
<td>6</td>
<td>3</td>
<td>36**</td>
</tr>
<tr>
<td>7</td>
<td>3</td>
<td>41**</td>
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<tr>
<td>8</td>
<td>3</td>
<td>44**</td>
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<tr>
<td>9</td>
<td>14</td>
<td>47**</td>
</tr>
<tr>
<td>10</td>
<td>17</td>
<td>50**</td>
</tr>
</tbody>
</table>

Key: a Entries in columns (5), (6) and (7) are M values, given period i profits of \( \pi_i = (\pi_i - \pi_c) / (\pi_M - \pi_c) \), where \( \pi_M \) equal maximum available monopoly profits, and \( \pi_c \) competitive profits. Asterisks indicate rejection of the null hypothesis that the measure in the column does not differ significantly from its counterpart in the TDSLO treatment, using a Fisher Exact Probability test. ** \( p < .05 \), * \( p < .10 \) (two-tailed tests).
TABLE 4.
Trend Demand Design. Price Deviations and Efficiency Extraction Rates.

<table>
<thead>
<tr>
<th>Period or Period Block</th>
<th>Mean Absolute Price Deviations (cents)</th>
<th>Mean Efficiency (%)</th>
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</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
</tr>
<tr>
<td></td>
<td>TDSLO</td>
<td>TDFAS</td>
</tr>
<tr>
<td>1</td>
<td>0.10</td>
<td>0.21</td>
</tr>
<tr>
<td>2</td>
<td>0.38</td>
<td>0.15</td>
</tr>
<tr>
<td>3</td>
<td>0.53</td>
<td>0.31**</td>
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<td>4</td>
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<tr>
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<tr>
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</tr>
<tr>
<td>7</td>
<td>0.96</td>
<td>0.27**</td>
</tr>
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<td>15</td>
<td>0.13</td>
<td>0.07**</td>
</tr>
</tbody>
</table>

Key: Asterisks indicate rejection of the null hypothesis that the measure in the column does not differ significantly from its counterpart in the TDSLO treatment, using a Mann-Whitney test. ** \( p < .05 \), * \( p < .10 \) (two-tailed tests). *Italicization* highlights periods following inflationary shocks, *bolding* highlights periods following deflationary shocks.
TABLE 5.

Swastika Design. Mean Price Deviations. Unit of time comparisons (cents).

<table>
<thead>
<tr>
<th>Period or Period Block</th>
<th>SWSLO (Periods)</th>
<th>SWFAS (Ten Period Blocks)</th>
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<td><strong>Excess Demand Regime</strong></td>
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</tr>
<tr>
<td>1</td>
<td>-119</td>
<td>-91**</td>
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<td>2</td>
<td>-94</td>
<td>-31**</td>
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<td>3</td>
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<td>-15**</td>
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<td>9</td>
<td>-17</td>
<td>-1**</td>
</tr>
</tbody>
</table>

| **Excess Supply Regime** |
| 10                     | 180            | 184                       |
| 11                     | 165            | 165                       |
| 12                     | 160            | 138                       |
| 13                     | 163            | 96**                      |
| 14                     | 156            | 88**                      |
| 15                     | 155            | 86*                       |
| 16                     | 146            | 68**                      |
| 17                     | 142            | 84                        |
| 18                     | 130            | 110                       |

*Key:* Each entry is the deviation of the mean transactions price from the competitive prediction. Asterisks indicate rejection of the null hypothesis that the measure in the column does not differ significantly from its counterpart in the TDSLO treatment, using a Mann-Whitney test. **p<.05, *p<.10 (two-tailed tests).
TABLE 6.

<table>
<thead>
<tr>
<th>Period or Cycle</th>
<th>(1) SWSLO (Periods)</th>
<th>(2) SWFAS1 (Periods)</th>
<th>(3) SWFAS2 (Every Second Period)</th>
<th>(4) SWFAS3 (Every Third Period)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Excess Demand Regime</td>
<td>119</td>
<td>153**</td>
<td>143</td>
<td>136</td>
</tr>
<tr>
<td>2</td>
<td>94</td>
<td>148**</td>
<td>105</td>
<td>63</td>
</tr>
<tr>
<td>3</td>
<td>79</td>
<td>140*</td>
<td>63</td>
<td>54</td>
</tr>
<tr>
<td>4</td>
<td>77</td>
<td>121**</td>
<td>60</td>
<td>42**</td>
</tr>
<tr>
<td>5</td>
<td>77</td>
<td>96</td>
<td>55</td>
<td>29**</td>
</tr>
<tr>
<td>6</td>
<td>61</td>
<td>75</td>
<td>42</td>
<td>24**</td>
</tr>
<tr>
<td>7</td>
<td>42</td>
<td>60</td>
<td>39</td>
<td>20</td>
</tr>
<tr>
<td>8</td>
<td>30</td>
<td>58*</td>
<td>24</td>
<td>21</td>
</tr>
<tr>
<td>9</td>
<td>17</td>
<td>57**</td>
<td>24</td>
<td>15</td>
</tr>
</tbody>
</table>

Key: Each entry is the deviation of the mean transactions price from the competitive prediction. Asterisks indicate rejection of the null hypothesis that the measure in the column does not differ significantly from its counterpart in the TDSLO treatment, using a Mann-Whitney test. **p<.05, *p<.10 (two-tailed tests).
FIGURE 1

<table>
<thead>
<tr>
<th>Seller ID</th>
<th>Standing Prices</th>
</tr>
</thead>
<tbody>
<tr>
<td>S1</td>
<td>$2.10 $1.80 $1.60 $2.00</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Seconds to Close</th>
<th>7</th>
</tr>
</thead>
<tbody>
<tr>
<td>Period</td>
<td>4</td>
</tr>
<tr>
<td>Unit</td>
<td>7</td>
</tr>
<tr>
<td>Unit Price Offer Qty Sales Qty</td>
<td>7</td>
</tr>
<tr>
<td>Cost</td>
<td>7</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Unit</th>
<th>Unit Price</th>
<th>Offer Qty</th>
<th>Sales Qty</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>$1.30</td>
<td></td>
<td></td>
</tr>
<tr>
<td>2</td>
<td>$1.40</td>
<td></td>
<td></td>
</tr>
<tr>
<td>3</td>
<td>$1.70</td>
<td></td>
<td></td>
</tr>
<tr>
<td>4</td>
<td>$2.00</td>
<td></td>
<td></td>
</tr>
<tr>
<td>5</td>
<td>$2.30</td>
<td></td>
<td></td>
</tr>
<tr>
<td>6</td>
<td>$2.70</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

| Period Earnings | $2.00 |
| Cumulative Earnings | $9.65 |

Current and Past Period Prices

Your Period Earnings

Current

Last Period
FIGURE 2
FIGURE 6

TDSLO

Price

TDFAS

Price

50
FIGURE 7

Sequences with Inflationary Shocks
Median Posted Price Deviations

Sequences with Deflationary Shocks
Median Posted Price Deviations

Mean Efficiency

Mean Efficiency

--- 1st --- 2nd --- 3rd --- 4th --- 5th --- 6th

--- 1st --- 2nd --- 3rd --- 4th --- 5th --- 6th
FIGURE 8

Price

$3.50
$3.00
$2.50
$2.00
$1.50
$1.00
$0.50
$0.00

0 1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18

Period

Price

$3.50
$3.00
$2.50
$2.00
$1.50
$1.00
$0.50
$0.00

0 10 20 30 40 50 60 70 80 90 100 110 120 130 140 150 160 170 180

Period

SWSLO

SWFAS