The Hayek hypothesis and long run competitive equilibrium: an experimental investigation

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Abstract

We report on an experiment investigating whether the Hayek Hypothesis (Smith, 1982) extends to the long run setting. We consider two environments; one with a common production technology having a U-shaped long run average cost curve and a single competitive equilibrium, and another with a constant long run average cost curve and multiple competitive equilibria. While there is convergence in both environments to the long run equilibrium, it takes longer and is less robust than usually observed in the short run setting. Price formation is adaptive and quickly converges to realized short run equilibrium, but long run investment decisions exhibit nominal rationality. We formulate and estimate an Markovian investment choice model incorporating this nominal rationality. We show this model, coupled with repeated decisions, is enough to achieve high long run allocative efficiency when markets use continuous double auctions.

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Keywords: Experiment; Double Auction; Hayek Hypothesis; Long Run Equilibrium; Bounded Rationality

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1 Introduction

Regarding the problem of optimally allocating productive resources, neoclassical economics unequivocally prescribes the adoption of decentralized market institutions that robustly implement competitive equilibrium outcomes. This prescription is rooted in the Pareto optimality of competitive equilibrium allocations (i.e., the first fundamental welfare theorem with appropriate convexity assumptions), and confidence in Hayek's (1945) conjecture that unfettered markets *implement* competitive equilibrium prices and allocations when consumers' and firms' information is decentralized and private. Smith (1962) provided the first demonstrative empirical evidence of this implementation ability in experiments that coupled decentralized private information of individual supply and demand with a continuous double auction trading institution. After 20 years of subsequent research on the double auction, Smith (1982) synthesized this research and argues it provides a strong induction[1] of what he coined the "Hayek Hypothesis."

However, much of this experimental evidence in favor of the Hayek Hypothesis is collected under the short run decision horizon of sellers. These experiments typically adopt a produce-to-order norm and "control" individual supply through an experimenter provided marginal cost schedule. Such a marginal cost schedule is synonymous with a single input production function and imposes cost minimizing behavior. Under these circumstances, the difficulty of coordination is low for the Hayek Hypothesis; buyers and sellers can achieve output and price coordination by simply evaluating whether the marginal benefits exceed the marginal costs for each proposed transaction.[2] In essence, we can't use these experiments to evaluate how well price information in the output good market leads to efficient allocation of inputs goods, and moreover the optimal number and scale of firms in the output market.

In this study, we experimentally test the Hayek Hypothesis when we extend the setting

[1] A half century after publication, Smith's experimental results have proven so reliable that classroom replications are now a common activity in modern economics curriculum.

[2] This idea forms the core principle of Gode and Sunder (1993), who argue that the double auction institution itself, not the rationality of traders, is the source of allocative efficiency in these market experiments.

from the short run to the long run decision horizon of sellers. In particular, sellers must commit to a level of a fixed input in advance of the market, and then produces-to-order in the short run. The conditions of competitive equilibrium in this long run setting extend to include price equating the minimum of long run average cost, sellers minimizing the cost of their output, sellers earning zero economic profit, and the number firms of entering the market. Production technology plays a crucial role in determining the value of these conditions, and is our sole experimental treatment variable. We consider two production technologies: one technology is represented by a standard textbook U-shaped long run average cost curve, and the other is constant returns to scale represented by a constant long run average cost function.

These two treatments present different challenges for the implementation of the long run competitive equilibrium (LRE, hereafter) as technology affects its determinacy, and the rationality required for cost minimization. With the U-shaped average cost curve technology the LRE is unique and each firm must choose the unique level of fixed input that is consistent with minimizing average cost. We call this the UNQ treatment. In contrast, with constant returns to scale there is a multiplicity of LRE in terms of the number of sellers and their sizes, as defined by the fixed input level. We call this the CRS treatment. In summary, the LRE is unique but requires all sellers to individually find the optimal production plan in the UNQ treatment, while in the CRS treatment there is a coordination problem presented by the multiplicity of LRE but only the aggregate production plan - not individual ones - need to be optimal.

The aggregate results from our experiment indicate that the Hayek hypothesis extends to the long run case even when there is a multiplicity of LRE. Allocative efficiency starts at about 90% and then rises to 95% in the UNQ treatment, but is surprisingly higher, between 96-98%, in the CRS treatment. A decomposition of the efficiency loss into trading and investment inefficiencies shows this difference arises from a lower investment efficiency in UNQ treatment.

The convergence to the LRE is slower than what others typically observe in short run settings; all of our sessions have initial over investment that slowly falls to LRE levels. Price adjustment is not the source of the tepid convergence, as price quickly adapts to changing short run supply conditions and tracks the short-run partial equilibrium. The main source of the sluggish convergence is the low levels of rationality and slow adjustment of sellers' long run investment decisions.

Sellers' investment choices coincide too little with the best responses to past or future prices to be modeled by random utility based equilibrium (Mckelvey and Palfrey, 1995) or adjustment (Camerer and Ho, 1999) models. The only rationality we find is that sellers are slightly more likely to change from their current investment levels to one as least as profitable than to one no more profitable. Incorporating this minimal rationality, we formulate and estimate a Markov model of investment choice dynamics. When we consider the estimated price and investment dynamics together we show that, in expectation, they track the dynamics of our experimental data including the tendency for cobweb type cycles in investment/firm size and prices around competitive equilibrium levels. Moreover, this demonstrates that in the presence of only a modicum of seller rationality with respect to long run decisions the double auction trading institution can generate highly efficient outcomes.

Other studies have also examined the economic performance of double auction markets with more enriched production, typically general equilibrium, settings. However, these studies all consider produce-in-advance and none consider the multiple equilibrium case like our CRS treatment. Perhaps the most striking difference between our results and theirs is they typically observe underproduction in the output market, and correspondingly relative output prices above equilibrium levels. One set of these papers (Hey and Di Cagno, 1998; Riedl and van Winden, 2007, 2012) adopts the following sequence of economic activity; markets for input goods, production, and then markets for output goods.[3] Notice a consequence of this

[3]Another fascinating experiment following this sequence is Crockett, Smith, and Wilson (2009) who replace the double auction institution with unstructured bargaining. Here there are two output goods and one input, households slowly and incompletely discover efficiency through trade and comparative advantage.

sequencing is that firms must bear the risk of purchasing all inputs prior to the realization of output prices, and then when entering the output market costs are sunk and short run supply is perfectly inelastic at the level of production. While these elements are not present in the definition of competitive equilibrium, they do have a significant impact on market outcomes. In these experiments there is under production of output goods, under utilization of input goods, and the ratio of input to output prices is below the equilibrium ratio. And there is no discernable movement towards competitive equilibrium.

A second set of double auction market papers considers experimental general equilibrium production economies where input and output goods are conducted simultaneously. Producers in these markets still must purchase the required input goods prior to the production of a unit of output. While the costs of produced output are still sunk in this setting, production can adjust upwards in response to current market period conditions. This seems to allow for full equilibration in simple one output good economies (Goodfellow and Plott, 1990; Bosch-Domènech and Silvestre, 1997) and movement towards equilibrium in complex economies with multiple input and output goods (Noussair, Plott, and Riezman, 1995, 1997, 2007). However, in all of these cases convergence still occurs from too little production and the ratio of input to output prices below the equilibrium ratio. The researchers conjecture this ratio reflects a risk premium demanded by the producers for having to produce in advance.

The consistent initial underproduction when the setting is produce-in-advance stands in strong contrast to the overproduction and over utilization of fixed inputs in our market. There is one example where produce-in-advance is also characterized by initial overproduction and convergence to equilibrium prices occurs from below. Mestelman and Welland (1987, 1988) take Smith's basic design but require sellers to choose output levels, and bear the cost, in advance of market trading. This suggests that initial underproduction in general equilibrium experiments may not result solely from the riskiness of produce-in-advance, as we now are seeing partial equilibrium is characterized by overproduction - inconsistent with the hypothesis of risk averse sellers.

2 Experimental design

2.1 Economic Environment

The experimental design is based on twenty-five market periods for a non-durable discrete good we benignly label "box". On the supply side of these markets is a constant set of eight sellers. On the demand side there is a constant set of eight buyers, whose demand for boxes is renewed each market period.

Regarding the sellers' decisions, we restrict our attention in three ways. First, sellers have a common technology that describes the feasible number of boxes that can be produced utilizing different combinations of two input goods. Second, the level of one of these input goods - the fixed input - must be determined prior to choosing levels of production and the other input good - the variable input. The choice of the fixed input level is made only in odd numbered periods and remains unchanged in the subsequent even numbered period. Third, the input good prices are exogenous and constant; our consideration is for the partial equilibrium of the box market.

The seller owns five durable units of the fixed input, which he allocates between the production of boxes and leasing at the exogenous per period price.[4] Leased units of the fixed input generate a stream of revenue each period we call a 'profit bonus.' For units allocated to the production of boxes, we call their market value 'investment.' A seller's 'fixed cost' is the opportunity cost of this investment. Explicitly, his fixed cost for a market period is the potential revenue from leasing all five of his fixed input units less the profit bonus received from the units he actually leases. Hence, we use the terms fixed cost and investment interchangeably. Given a fixed input level, there is a minimum total variable input requirement schedule for the various possible production levels of boxes that, in conjunction with the exogenous variable input price, generates a short run marginal cost schedule.

In further discussions and in our experiment design we frame a seller's *long run decision*

[4]Note, we prohibit a seller from increasing his stock of the fixed input by renting in this market.

as a choice from a menu of profit bonuses and associated marginal cost schedules. This menu gives rise to a family of short run average total cost curves, the lower envelope of which constitutes the firms' long run average costs. We present subjects the cost function description of the technology, rather than its dual production function description, because of its descriptive simplicity and close correspondence to the extensive experimental economics markets literature which typically frames supply as a schedule of unit (marginal) costs.

Seller technology is our treatment variable and we consider two types. First, our UNQ treatment adopts a discrete example of a U-shaped long run average cost curve technology. This is presented in Panel A of Table 1, which shows four possible short run marginal cost schedules along with associated investment levels/profit bonuses. Cost schedule #5 coincides with exiting the market: the investment is zero and the production of boxes is impossible. The plot of the family of short run average total cost curves is presented in Figure 1, and the long run average cost curve is the lower envelope of these curves. Notice long run average cost is minimized at 118 by choosing cost schedule #3 and producing six boxes.

Second, our CRS treatment adopts a discrete example of constant returns to scale technology, presented in Panel B of Table 1. Again there are four alternative short run fixed/marginal cost pair schedules, with cost schedule #5 corresponding to an exit from the market. Figure 2 presents the CRS family of short run average total cost curves. Notice for each possible level of investment, the corresponding short run average total cost curve is minimized at 118. Furthermore, each of these minimum points occurs at an output quantity that is a multiple of three. This is the source of indeterminacy in the market composition of firms when solving for market supply. For example, at the price of 118 the total amount of profit earned by two firms is the same when one firm produces six boxes using cost schedule #3 and the other firm exits, or both firms produce three boxes each using cost schedule #4.

The market demand for boxes is constant for each market period and is calculated by horizontal summation of the eight individual demands. Table 2 presents these individual demand curves as schedules of unit valuations. During the experiment, we shuffle each of these schedules among the buyers each period. Thus, while subjects observe their own individual demand schedules changing, the market demand remains constant.

We specified the cost parameters of the UNQ and CRS treatments to make their respective long run equilibria coincide as closely as possible. A LRE is defined by several conditions. First, the market price must equate short run quantity demanded and quantity supplied. This price must also exceed the minimum of the LRAC, but not so much that it would be more profitable to increase investment. Prices in the interval [118,119] satisfy these criteria for our experiment. Second, the LRE quantity of boxes traded is 48. Third, in a LRE all sellers earn zero economic profits (or slightly positive due to the discreteness of the environment), which corresponds in our experiment to nominal profit in the range [800,806] each period.

The LRE of the UNQ and CRS treatments differ in the fourth equilibrium condition concerning the investment profile. For the UNQ treatment, the unique equilibrium investment profile has every seller investing 400, i.e. choosing cost schedule #3. On the other hand there is a multiplicity of equilibrium profiles in the CRS treatment. Since sellers' individual fixed inputs are perfect factor substitutes in the aggregate production of boxes, any investment profile for which the sum of the individual investments equals 3200 is an equilibrium investment profile. All together there are 33 such equilibrium investment profiles.

2.2 Experimental Institution and Procedures

Subjects' perform two types of decision tasks. First, prior to the odd numbered market periods, each seller must select one item from a menu of five possible profit bonus-unit cost schedule pairs. This choice is made without time constraint, nor knowledge of what other sellers' choices are. This is executed from a pop-up window within the computer program used to run the experiment.[5]

The second component is the subjects' participation in the 25 computerized double auc-

[5] An online appendix for this paper at http://www.jasonshachat.net/LREAppendices.pdf provides screen captures of the computerized instructions and interface in both English and Mandarin.

tion periods for trading boxes. Each trading period lasts 165 seconds. During the double auction buyers and sellers can respectively submit limit bids and limits asks (or simply bids and asks) for a single unit, although a subject can submit multiple such limit orders. The order book of currently available bids and asks is open; i.e., the full order book is displayed on every subject's computer interface. There is a bid/ask improvement rule, a new bid/ask must exceed/decrease the current highest bid/lowest ask. A trade occurs whenever (1) a buyer submits a bid higher than the current lowest ask, or (2) a seller submits an ask lower than the current highest bid. A trade eliminates the associated order from the book.

Every subject's display contains a market trade summary region providing a sequential plot of trade prices, the last trade price, the average trade price in the period, and the number of trades for the period. This trade summary by default shows information for the current period, but can easily be adjusted to show the same information for any past period.

A key element of experimental economic methodology is the technique of induced value (Smith, 1976) which we use to establish control over the supply and demand conditions of the market. Individual demand is induced by allowing a buyer to accrue earnings in the experimental currency equal to his unit valuation less the price paid for each box purchased. Individual supply is induced by allowing a seller to accrue earnings in the experimental currency through the collection of profit bonuses and by the price collected for each box sold less the associated unit cost. At the conclusion of an experimental session, a buyer's and a seller's earnings are converted to the local currency, the Chinese yuan, at an exchange rate of 50 to 1 and 1000 to 3, respectively.[6]

We conducted all of our experimental sessions at the Finance and Economics Experimental Laboratory (FEEL) at Xiamen University. We ran 8 sessions for CRS treatment and another 8 sessions for UNQ treatment. All 256 (8 buyers and 8 sellers for each session) subjects were students attending Xiamen University, with about equal numbers of undergraduate and Master degree students, and were recruited using the ORSEE Online Recruitment

[6]We chose the exchange rates so that, in equilibrium, a buyer's and a seller's expected earnings in Chinese Yuan are the same.

System (Greiner, 2004).[7] The experiment itself was conducted using the BASA software developed by the IBM TJ Watson Research Center. This software uses an interactive set of computerized instructions that the subjects read individually.[8] After all subjects completed reading the instructions at their own pace, we conducted two market periods for practice which we publicly announced were not for pay. Afterwards, we conducted 25 periods which we announced were for pay. Table 3 reports the ranges and standard deviations of subject payments by role and treatment. The average buyers' payments are larger than the average sellers' payments because of disequilibrium outcomes in which consumer surplus exceeds, and producer surplus fails to meet, LRE levels.

3 Evaluating the Hayek Hypothesis

We start by providing a data visualization of an experimental session that depicts realized short run market supply schedules, trade prices, and quantities against the respective LRE theoretical benchmarks. Figure 3 is this visualization for our UNQ treatment session UNQ08, and is a 4×3 array of data plots. Each plot consists of the data from pairs of market periods that follow each long run decision made by the sellers (due to space limitation we have omitted market periods one and two.) The fixed elements in these plots are the induced market demand schedule, a vertical line at the LRE quantity of 48, a horizontal line marking the LRE price of 118, and the short run market supply schedule that arises in the LRE when all sellers choose the investment level 400. There are three dynamic elements in each data plot: (1) the realized short run market supply schedule given by the lighter colored increasing step function, (2) the transaction price sequence of the first market period given by the open circles, and (3) the transaction price sequence of the second market period

[7]At the time we ran our sessions, the subject data base contained approximately 1200 students in the subject pool. From this subject pool a sub-sample of potential participants, filtered for previous participation in this study, was invited to attend a specific session along with an explanation that they would receive a 10 Yuan show-up fee, possibly earn more money through their participation in the experiment, and that the session would last no more than 2.5 hours.

[8]As this experiment is an investigation of market performance under decentralized private information, we did not publicly display or read any part of the instructions.

denoted by the crosses. This session is typical[9] in that prices generally converge quickly to the current short run market equilibrium by the second half of the experiment, and the quantity traded coincides with the short run equilibrium. With respect to the long run we observe that the short run supply converges closely, but not exactly, to the LRE predictions, and correspondingly price and quantity also converge close to their LRE predictions. Overall, it appears the Hayek hypothesis extends to the long run situation for the UNQ technology.

Figure 4 provides the same data visualization for CRS treatment session CRS02.[10] We again note that within market period prices adjust to the short run competitive equilibrium. With respect to the LRE, price and quantity appear to move to neighborhoods around the LRE predicted values as well, but there is less stability in the convergence of the short run supply schedule; the figure suggests a cobweb-like dynamic.

3.1 Evaluation of microeconomic system performance

We now address whether the robustness of the Hayek hypothesis extends to the long run by comparing observed price, market quantity, market level investment, seller's profit, and allocative efficiency to their respective LRE values. In Table 4 we report the means of these variables for the first and second halves of the experiment. Then, in Figure 5, we provide a more detailed time series comparison for some of these variables.

According to the Hayek Hypothesis, price is the key variable which drives market efficiency. While prices in both treatments are significantly below the LRE level for the first halves of the sessions, we can't reject these prices are at the LRE level in the second halves of the sessions. If we consider the time series of average prices, the upper left corner of Figure 5, we see that prices in both treatments converge to the LRE levels from below and the LRE predicted prices are almost always contained within the period-by-period 95% confidence intervals. Realized market quantities fall in line with the LRE as observed prices do. In the

[9] The online appendix for this paper at http://www.jasonshachat.net/LREAppendices.pdf contains this figure for all experimental sessions.

[10] Due to the indeterminacy of the short run market supply, the benchmark supply curve is the average 33 cost schedules associated with the set of equilibrium investment profile.

first half of the sessions the quantity is statistically larger than 48 for both treatments but in the second half of the sessions both of the mean quantities are not significantly different from 48. This convergence is also suggested by the time series presented in the upper right corner of Figure 5.

We take a first coarse look at the seller's investment decisions and profits. We consider average investment levels[11] in Table 4 and Figure 5 where we see that in both treatments there is early over investment that slowly declines to the LRE average level of 400. Further, we see in the same table and figure that average seller profit starts well below the exit-the-market level of 800 and adjusts in the same slow way average investments does to the LRE level. Thus, the Hayek hypothesis does seem to hold with enough long run decision repetitions, but at the same time the opportunity cost message contained in market price does not seem to resonate with the investment decisions as much as it does with the bargaining and output decisions in the short run. Investment choice dynamics warrant closer consideration.

The final performance variable we consider is allocative efficiency, which is the ratio of the realized gains of buyers and sellers and the maximum potential gains from exchange. We see that, in Table 4, the allocative efficiency improves from approximately 92% to 95% from the first halves to the second halves of sessions for the UNQ treatment, and there is insignificant improvement from 97% to 98% in the CRS treatment. In both cases, confirmed in unreported hypothesis tests, the allocative efficiency is higher in the CRS case.

Because of the long run decision element of our experiment, two distinct factors determine the level of allocative efficiency, AE, in our markets: (1) the degree that buyers and sellers maximize potential earnings conditional upon the realized short run market supply, and (2) the degree that the sellers choose efficient investment levels. We measure total realized gains, RG, as the sum of the of the sellers' and buyers' earnings in the double auction market and the total of the sellers' collected profit bonuses. Maximum potential gains, MLR, is similarly calculated as the sellers' and buyers' market earnings and the sum of the sellers'

[11]The average is a somewhat erroneous simplified measure in the UNQ case; later we consider the whole investment profile.

profit bonuses in the LRE. Now define MSR as the maximum possible gains given the seller's investment profile.[12] By definition,

$$AE = \frac{RG}{MLR} \equiv \frac{RG}{MSR} \times \frac{MSR}{MLR}.$$

Call the two right hand terms trading efficiency, TE, and investment efficiency, IE, respectively. Further denote the efficiency loss for each respective measure as LTE, and LIE. We decompose the loss in AE as follows.

$$AE = TE \cdot IE = (1 - LTE)(1 - LIE), \text{ or } LTE + LIE + AE \approx 1.$$

For each treatment, we calculate the average of the three terms for each market period across the 8 sessions.[13] These results are plotted in Figure 6. From this figure we observe that,

1. in every period, allocative efficiency is higher in CRS treatment than in UNQ treatment;
2. the difference is mostly attributed to lower investment efficiency loss in CRS treatment;
3. there is a slow but steady increasing trend in allocative efficiency in UNQ treatment resulting from the steady decrease in investment efficiency loss;
4. and efficiency loss from trading is about 2%, which reflects the typical high performance of double auction mechanism in realizing exchange gains in short run markets.

Summarizing the results on market performance, our experiments provides strong evidence that the Hayek hypothesis extends from the scope of Smith's original short run partial equilibrium setting to our long run one. This even holds true for the CRS case with multiple equilibria. However, there are some caveats we need to address. Why is there greater investment inefficiency in the UNQ versus CRS treatment? Further markets clearly adjusts slowly from over-investment in the early periods to the LRE. What are the underlying behavior principles and choice dynamics governing market prices and investment profiles that give rise to such slow adjustment?

[12] The ratio of RG to MSR is the allocative efficiency measure often reported in experimental studies of short run markets.

[13] The term we drop from the approximation has little impact in almost all periods because both LTE and LIE are less than 5%, so the product of them is no more than 0.25%.

4 Price and Investment Dynamics

Price and investment are two key endogenous variables in our experimental market. In this section we present and estimate dynamic models of both variables. Then we show the estimated pricing and investment profile models together converge to the LRE predictions.

4.1 Price dynamics

To model the inter-period dynamics of trading prices, we utilize the fact that the current investment profile determines the short run equilibrium price (and quantity) and assume prices adjust proportionally to their deviation from the equilibrium. This leads us to estimate the following distributed lag model:

$$\bar{P}_{s,t} - \bar{P}_{s,t-1} = \alpha_s + \beta \left(\bar{P}_{s,t-1} - P^e(\boldsymbol{I_{s,t}}) \right) + u_{s,t}$$

in which $\bar{P}_{s,t}$ is the average trading price in period t of session s, $\boldsymbol{I_{s,t}}$ is the 8-element investment profile in period t of session s, and P^e is a function that returns the equilibrium price when the short run market supply is determined by $\boldsymbol{I_{s,t}}$. We report the fixed effects estimation of this model for our two treatments in Table 5. Note that for both regressions F-tests fail to reject the joint hypothesis all fixed effects are jointly zero, and a pair of White tests fail to reject that the error terms are homoscedastic.

The regression results suggests that when the market investment profile changes, the expected average price in the subsequent market does not equal the new short run equilibrium price because $\beta \neq 0$. In both treatments the estimated β is about one-third. This suggests if investment profiles are constant across periods, we can expect geometric convergence to equilibrium prices.

4.2 Investment dynamics

In the previous section we showed average investment across sessions started above the LRE level of 400, and over the 13 investment decisions made within a session converged to the LRE levels. We now provide a more detailed view of investment dynamics and present a boundedly rational model of investment choice. Let's start by examining individual investment decisions within our example sessions UNQ08 and CRS02, which we present in Figure 7. In each of the panels of this figure, the columns labeled A through H represent the decisions made by 8 sellers sorted from the lowest average investor to the highest. Each row represents the selected investment profile for the period given in the leftmost column. We shade an individual seller's pie according to his investment level as follows: an empty pie for 0 (a market exit); a one-quarter pie for 200; a one-half pie for 400; a three-quarter pie for 600; and full pie for 800. For the CRS session the column labeled 'Avg' gives the average investment for that period. The two rightmost columns give, for the subsequent even-numbered period[14], the average price and market quantity of boxes sold. The bottom row gives the average period total earnings for each seller.

Figure 7 exhibits several features that suggest many investment choices are not optimal. First it is clear that when prices are below the LRE level of 118 in an even numbered period, most sellers do not exit the market in the subsequent odd numbered period. Second, in the last three investment decisions of the UNQ session, even after price converges around the LRE level only a minority of the sellers select the optimal investment level of 400. Third, when individuals do adjust their investment level it is often with smallest possible adjustment size. There are a couple of exceptional individuals in the CRS session who seem to only switch between exit and the maximum investment of 800. This is reflected in the average investment level following a possible cobweb pattern. We now quantify how suboptimal individual investment decisions are for much of the experiment.

[14]For period 25, the last trading period, the average price and quantity are for that period itself.

4.2.1 How rational are investment choices?

To assess the extent investment choices are optimal we first consider a myopic best response benchmark. Let $\pi(p, I)$ be a seller's profit function, i.e. the level of profits at the profit maximizing output level, for price p and investment level I. Now when considering the value of alternative I's we assume a seller uses this profit function and some price expectation. When assessing the extent subjects rationally choose investment, we set this price expectation to the average price from the previous period $\bar{p}_{t-1}$. However, we note our following results are robust to this choice. In unreported analysis, we show find is essentially no difference if we set this price expectation as the average of the previous two period prices, the previous closing price, or we assume sellers are forward looking with rational expectations and set p equal to the average price of the subsequent period.

Let's consider how often a seller i's investment choice I_{it} agrees with the following best response condition

$$\pi(\bar{p}_{t-1}, I_{it}) \geq \pi(\bar{p}_{t-1}, k), \text{ for all } k \in \{0, 200, 400, 600, 800\}.$$

Starting from period 3, we calculate for each investment decision the proportion of sellers' choices satisfying this best response criteria. Figure 8 reports the time series of this proportion for each treatment. The proportion of best response starts below 10% for both treatments. Over the course of the eleven subsequent investment choices the best response in the UNQ treatment rises slowly towards 40%, and in the CRS treatment the proportion appears to level off at slightly above 20%. To appreciate how low these proportions are, consider a subject who randomly selects one of the five possible investment levels with equal probability. Under this choice rule the expected best response rate would be 20%. It appears that sellers are doing worse than this pure random benchmark for the first half of the experiment, and it begs the question whether investment choice exhibits rationality of any standard?

We attempt to find rationality by looking for more muted demonstrations of improving choice. We consider a subject's choice of current investment relative to their previous investment level, and simply ask whether sellers are more likely to transit to an investment level offering higher profit than to one offering lower profit. Specifically does the following inequality hold,

$$\Pr\left(I_{it} \in \{k|\pi(\bar{p}_{t-1}, k) \geq \pi(\bar{p}_{t-1}, I_{it-1})\}\right) \geq \Pr\left(I_{it} \in \{k|\pi(\bar{p}_{t-1}, k) \leq \pi(\bar{p}_{t-1}, I_{it-1})\}\right).$$

Consider three type of investment transitions: a 'better' investment transition is a switch to an investment offering strictly higher profit or maintaining the current investment level if it is the profit maximizing one, a 'same' investment transition is maintaining a non-profit maximizing investment level; and a 'worse' investment transition is a switch to one that offers a strictly lower profit. In Figure 9, we show for each treatment the proportion of each type of investment transition by period. From inspection of this figure, we can see that proportion of better transitions is slightly higher than worse transitions, there is also a large proportion of inertia with same transitions, and there is no discernable trend.

4.2.2 A Markov model of boundedly rational investment choice

We now present a boundedly rational model of investment choice. We first note that while stochastic best response is common component of behavioral decision making models, it is not appropriate here. Stochastic best response dictates that alternatives yielding higher value are chosen with greater probability, and this has been proven effective when used in stochastic equilibrium models, such as Quantal Response Equilibrium (Mckelvey and Palfrey, 1995), and learning models, for example Experienced Weighted Attraction (Camerer and Ho, 1999). However, we have already shown investment decisions are inconsistent with the higher value implies higher choice probability premise of stochastic best response. Instead we use a coarse version of the direction learning theory of Selten and Stoecker (1986). Direction learning is a state dependent principle that individual increases the likelihood of choosing an action that would have ex post yielded a higher reward than the current action. Our approach is more coarse in that the transition probability is only higher for the *set* of ex post more profitable actions, and the probabilities of transiting to the ex post better than and worse than sets are constant rather than proportional to the ex post differences in payoffs.

Incorporating the observed minimal rationality of investment decisions, we formulate and estimate a first order Markov model of investment choice dynamics. The transition probabilities from the previous investment level to the five possible levels depends upon two factors. First, there is higher likelihood of choosing from the set of investment levels offering higher ex post profits rather than from the set offer lower ex post payoffs. Second, there is a bias for transitions to levels that are of smaller rather than larger absolute changes.

We postulate a two stage process to determine the transition probabilities between investment levels. In the first stage, probability is allocated to between two subsets of possible investment levels: NW, the subset of investment levels no worse than I_{it-1}, and NB, the subset of investment no better than I_{it-1}. Specifically,

$$NW(\bar{p}_{t-1}, I_{it-1}) = \left\{k \in \{0, 200, 400, 600, 800\} | \pi(\bar{p}_{t-1}, k) \geq \pi(\bar{p}_{t-1}, I_{it-1})\right\}, \text{ and}$$
$$NB(\bar{p}_{t-1}, I_{it-1}) = \left\{k \in \{0, 200, 400, 600, 800\} | \pi(\bar{p}_{t-1}, k) \leq \pi(\bar{p}_{t-1}, I_{it-1})\right\}.$$

Note that NW and NB are not mutually exclusive as they will share at least the previous investment level as a common element. We assume that an α measure of probability is allocated to the NW set and a $1 - \alpha$ measure of probability is assigned to the NB set.

In the second stage probability measure is allocated amongst the elements within each of these sets. We allow for this allocation to reflect sellers possibly favoring investment levels having a smaller difference with the current level. Specifically probability is allocated according to the number of steps between an element and the previous investment level. We define the step count between investment levels j and k as,

$$s(j,k) = \frac{|j-k|}{200} + 1.$$

For example, the number of steps between an investment level and itself is 1, and the number of steps between investment levels 0 and 800 is 5. We use the following weighting function to determine an investment level's assigned share of probability measure,

$$w(j|I_{t-1}, Z, \lambda) = \frac{s(j, I_{t-1})^{\lambda}}{\sum_{k \in Z} s(k, I_{t-1})^{\lambda}},\ \forall j \in Z$$

in which Z is either the NW or NB set. In this proportional assignment, $\lambda \leq 0$ measures the strength of the bias for small investment changes within the set Z. When $\lambda = 0$, each element of the set is allocated an equal probability measure, and as λ decreases there is a corresponding growing bias. Now we can calculate the transition probability for each investment level by adding up the probability measures it is allocated from the NW and NB sets;

$$\begin{aligned}\Pr(I_t = j|I_{t-1}) = \alpha X_{(j \in NW(\bar{p}_{t-1}, I_{t-1}))} w(j|I_{t-1}, NW(\bar{p}_{t-1}, I_{t-1}), \lambda) \\ + (1-\alpha) X_{(j \in NB(\bar{p}_{t-1}, I_{t-1}))} w(j|I_{t-1}, NB(\bar{p}_{t-1}, I_{t-1}), \lambda),\end{aligned}$$

where X_{ω} is an indicator function for the event ω. Notice that investment inertia has two sources; the previous investment level receives probability from its inclusion in both the NW and NB set, and through the within set allocation bias regulated by λ.

Consider an example with the CRS treatment. Suppose the previous price is strictly less than 118, and the previous investment level is 400. Figure 10 shows schematically the two stage process. In the example $NW = \{0, 200, 400\}$ and $NB = \{400, 600, 800\}$, and probability α and $1-\alpha$ is assigned to each respective set. Then each set's probability is allocated amongst its elements as determined by λ. Table 6 gives the full transition probability matrix for the CRS treatment when $p < 118$. The transition probabilities for our example are given by the forth row of the table.

We estimate the two parameters of the Markov investment choice model for each treatment by maximum likelihood estimation and present them in Table 7. The two estimates of α are encouragingly similar, the magnitude of approximately 60% indicates that subjects are more likely, but not overwhelmingly so, to move into their current NW set. The estimate of λ is larger in magnitude for the CRS treatment than the UNQ treatment. However, in both cases the parameter estimate is significant and we reject that they there is no bias, i.e. $\lambda = 0$.

We investigate the dynamics on the market investment portfolio by examining the estimated Markov transition probability matrix at alternative price levels. Since sessions in our experiment typically start off with over investment and price below the LRE of 118, let's examine the estimated Markov transition matrices, presented in Table 8 for the UNQ and CRS treatment at the price of 115. The inertia in investment choice is reflected in the magnitude of the elements of the main diagonals of the matrices, which are much higher than any of the off-diagonal elements. The upper-left most element is the probability that a seller who has exited the market to continue to do so - which is the profit maximizing choice at the price of 115 - and is almost 75% for both treatments.

4.3 Joint price and investment dynamics

We conclude our analysis by combining our estimated models of inter-period price and investment choice dynamics. For each treatment we take the average initial investment profile and average prices in period 1 across the eight session as the initial condition. Then we extrapolate the expectation of the investment portfolio and average period price by successively applying the estimated Markov investment model and then the estimated inter-period price dynamic equation for two periods until we have forecasted up to period 30. In Figure 11, we present four views of this exercise's results for the UNQ treatment. The upper left plot tracks the predicted evolution of average price (y-axis) versus average investment (x-axis). The predicted path strongly suggests the primary pattern in the data; slow adjustment from large initial over investment that converges to LRE levels after 10-15 periods. The bottom row of this figure shows the time series of price and average investment separately, and clearly shows this convergence as well as a small cobweb cycle in the investment - although this is in expectation and maybe difficult to observe in practice. The upper right corner shows the evolution of the investment profile which, for the UNQ treatment in particular, is more informative than average investment. This plot exhibits some interesting dynamics as the first ten periods show increasing adoption of the two lowest investment levels and decreasing adoption of the three highest investment levels. Then after price rises above 118, we see the profile proportions adjust towards a steady profile. In this equilibrium we observe that the optimal investment level of 400 is adopted with a proportion of 0.37 and the other levels equally share the remaining proportion. Thus, we can see this distribution of over-investment leads to a residual investment inefficiency in the UNQ treatment, and at the same time we still observe convergence to the LRE levels of price and average investment.

We present the results of the same exercise for the CRS treatment in Figure 11. The results here regarding convergence are the same, except there is an even more well defined convergence to a cob-web in both prices and investment. We find these figures encouraging as we casually observe noisy instances of such cycles in the data. Inspecting the investment profile evolution reveals a very interesting cycle between the investment levels 800 and 0, as the price oscillates above and below 118. This cycle is consistent with more rational stochastic best response, despite the investment model being formulated with a weaker Markov better response dynamic. Overall, combining the adaptive price formation model with the boundedly rational model does a striking job of mimicking the dynamics of the experimental data as it converges to the LRE. Furthermore, it provides an demonstration of how a behavioral rule, incorporating minimal rationality, used in conjunction with the double auction trading institution robustly generates LRE outcomes.

5 Discussion

We asked, can economies in which markets have the typical defined long run and short run production horizons with a common decentralized allocation process implement competitive equilibrium allocations? We sought to give the greatest chance of finding an affirmative response to this question by looking to extend the most celebrated result in experimental economics: Smith's (1962, 1982) discovery that for simple short run markets with decentralized private information, competitive outcomes robustly occur when trade is conducted through a continuous double auction. We found in long run case with a U-shaped long run average cost curve, replication of the market leads to the competitive LRE. However, this convergence is slower than in previous short run tests. We further stretched the boundary for which we know the Hayek hypothesis holds by conducting experiments with a constant returns to scale environment that introduces a multiplicity of equilibrium. Surprising, convergence to equilibrium was no more problematic in this case; moreover, there was higher efficiency.

A difficulty for sellers in the long run case is the need to synthesize the economic information conveyed in prices generated in the short run, to inform the decision of how much resources to commit in the long run. This is in contrast to a seller in a short run who only needs to assess whether the marginal revenue opportunity of the next unit exceeds the marginal cost. Perhaps it is not surprising that sellers do a miserable job of making optimal investment decisions, and are only slightly more likely to improve their investment decisions than not. What is surprising, is that such minimal rationality leads to long run efficiency with no more than 10 long run horizons. This result raises the question whether the results of models such as Hurwicz, Radner, and Reiter (1975) and Fehr and Tyran (2005) can be extended to allow for the lower levels of rationality we document and then model.

Obviously, ours is the first step to experimentally study the implementation of competitive equilibrium in markets with short and long run production decisions. Natural, but not yet answered, questions are whether comparative statics of the LRE will hold for things such a demand shocks, price changes with respect to the fixed and variable inputs, and also technological changes in production. Further extensions are warranted to the general equilibrium case in which the price and allocation of fixed inputs are determined periodically, to better understand the paradox of initial under production observed in other experiments and the overproduction we observe.

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Table 1: Menus of cost/investment schedules for the UNQ and CRS treatments

Panel A: UNQ Treatment

Cost Schedule #	Invest-Investment	Profit Bonus	Box #01	Box #02	Box #03	Box #04	Box #05	Box #06	Box #07	Box #08	Box #09	Box #10	Box #11	Box #12	Box #13	Box #14	Box #15	Box #16	Box #17
1	800	0	3	10	18	27	38	50	66	82	99	120	141	162	185	214	244		
2	600	200	8	15	25	37	49	62	80	101	124	162	202	246					
3	400	400	14	22	35	52	76	109	143	178	215	255							
4	200	600	28	53	103	153	203	254											
5	0	800																	

Panel B: CRS Treatment

Cost Schedule #	Invest-Investment	Profit Bonus	Box #01	Box #02	Box #03	Box #04	Box #05	Box #06	Box #07	Box #08	Box #09	Box #10	Box #11	Box #12	Box #13	Box #14	Box #15	Box #16	Box #17
1	800	0	2	8	16	24	33	43	53	64	75	87	99	112	124	138	151	164	178
2	600	200	3	12	22	35	48	62	77	93	110	127	144	162	181				
3	400	400	5	20	38	59	81	105	131	158	185								
4	200	600	12	49	93	144	200												
5	0	800																	

Table 2: Individual demand - unit valuation schedules

Schedule	Box #01	Box #02	Box #03	Box #04	Box #05	Box #06	Box #07	Box #08	Box #09	Box #10	Box #11
d1	148	146	143	139	132	119	117	101	98	97	95
d2	148	146	143	137	130	126	108	106	98	97	95
d3	148	146	143	137	130	126	108	106	98	97	95
d4	148	146	143	135	128	128	117	104	98	97	95
d5	148	146	143	135	133	126	113	104	98	97	95
d6	148	146	143	141	133	123	113	103	98	97	95
d7	148	146	143	141	133	119	110	103	98	97	95
d8	148	146	143	139	132	123	110	103	98	97	95

Table 3: Summary statistics of payments to participants
Unit: Chinese Yuan

Treatment	Subjects	Min	Max	Mean	Std. Dev.
CRS	Buyer	44	134	87.1	17.6
CRS	Seller	58	74	66.5	3.00
UNQ	Buyer	37	179	81.4	24.8
UNQ	Seller	48	73	64.5	5.50

Table 4: Means of various economic performance statistics

Variable	LRE Prediction	UNQ		CRS	
		Per. 1-12	Per. 13-25	Per. 1-12	Per. 13-25
Price[a]	[118,119]	107.39**	120.19	106.34**	117.62
Quantity	48	51.16**	48.01	54.40**	49.03
Average Investment	400	494.79**	434.38**	472.92**	412.50
Seller Profit	[800,806]	665.93**	771.99**	704.13**	787.06**
Allocative Efficiency	100%	92.18%**	95.03%**	97.11%**	98.16%**

[a] Mean price is calculated by first calculating the average price of each period, then averaging across sessions and periods of interest. This avoids overweighing lower prices which correspond to higher quantity periods.

** The difference from the LRE predicted value is significant at the 5% level; if the LRE prediction is an interval, this mark means that the average value is either significantly larger than the upper bound or smaller than the lower bound of the interval.

Table 5: Price dynamics from period to period

	UNQ		CRS	
Variable	Coefficient	t-stat	Coefficient	t-stat
Dummy session 1	1.09	1.03	-1.18	-1.33
Dummy session 2	1.30	1.23	0.69	0.79
Dummy session 3	1.92	1.81	0.38	0.43
Dummy session 4	-1.50	-1.36	0.64	0.73
Dummy session 5	0.41	0.39	-0.93	-1.06
Dummy session 6	0.55	0.52	0.55	0.63
Dummy session 7	-0.87	-0.77	-0.04	-0.05
Dummy session 8	0.87	0.81	0.31	0.35
$\bar{P}_{s,t-1} - P^e(\boldsymbol{I_{s,t}})$	-0.32	-9.72	-0.32	-11.33
Adjusted R^2	0.34		0.40	
F-test that	F-stat	p-value	F-stat	p-value
$\alpha_1 =, \dots, = \alpha_8 = 0$	1.15	0.33	0.60	0.78
White test for	χ^2_{17}-stat	p-value	χ^2_{17}-stat	p-value
Homoscedasticity	15.33	0.50	13.08	0.73

Table 6: Transition probability matrix for CRS treatment when price is lower than 118

I_{t-1}	$I_t = 0$	$I_t = 200$	$I_t = 400$	$I_t = 600$	$I_t = 800$
0	$\alpha + (1-\alpha)\frac{1^\lambda}{\sum_{j=1}^{5} j^\lambda}$	$(1-\alpha)\frac{2^\lambda}{\sum_{j=1}^{5} j^\lambda}$	$(1-\alpha)\frac{3^\lambda}{\sum_{j=1}^{5} j^\lambda}$	$(1-\alpha)\frac{4^\lambda}{\sum_{j=1}^{5} j^\lambda}$	$(1-\alpha)\frac{5^\lambda}{\sum_{j=1}^{5} j^\lambda}$
200	$\alpha\frac{2^\lambda}{\sum_{j=1}^{2} j^\lambda}$	$\alpha\frac{1^\lambda}{\sum_{j=1}^{2} j^\lambda} + (1-\alpha)\frac{1^\lambda}{\sum_{j=1}^{4} j^\lambda}$	$(1-\alpha)\frac{2^\lambda}{\sum_{j=1}^{4} j^\lambda}$	$(1-\alpha)\frac{3^\lambda}{\sum_{j=1}^{4} j^\lambda}$	$(1-\alpha)\frac{4^\lambda}{\sum_{j=1}^{4} j^\lambda}$
400	$\alpha\frac{3^\lambda}{\sum_{j=1}^{3} j^\lambda}$	$\alpha\frac{2^\lambda}{\sum_{j=1}^{3} j^\lambda}$	$\frac{1^\lambda}{\sum_{j=1}^{3} j^\lambda}$	$(1-\alpha)\frac{2^\lambda}{\sum_{j=1}^{3} j^\lambda}$	$(1-\alpha)\frac{3^\lambda}{\sum_{j=1}^{3} j^\lambda}$
600	$\alpha\frac{4^\lambda}{\sum_{j=1}^{4} j^\lambda}$	$\alpha\frac{3^\lambda}{\sum_{j=1}^{4} j^\lambda}$	$\alpha\frac{2^\lambda}{\sum_{j=1}^{4} j^\lambda}$	$\alpha\frac{1^\lambda}{\sum_{j=1}^{4} j^\lambda} + (1-\alpha)\frac{1^\lambda}{\sum_{j=1}^{2} j^\lambda}$	$(1-\alpha)\frac{2^\lambda}{\sum_{j=1}^{2} j^\lambda}$
800	$\alpha\frac{5^\lambda}{\sum_{j=1}^{5} j^\lambda}$	$\alpha\frac{4^\lambda}{\sum_{j=1}^{5} j^\lambda}$	$\alpha\frac{3^\lambda}{\sum_{j=1}^{5} j^\lambda}$	$\alpha\frac{2^\lambda}{\sum_{j=1}^{5} j^\lambda}$	$\alpha\frac{1^\lambda}{\sum_{j=1}^{5} j^\lambda} + (1-\alpha)$

Table 7: Parameter estimates in the Markov investment choice model

	UNQ	CRS
α	0.614	0.604
std. err.	0.0239	0.0234
λ	-0.483	-0.665
std. err.	0.0818	0.0838

Table 8: Estimated Markov transition matrix when price is 115

		UNQ					**CRS**				
		$I_t = 0$	200	400	600	800	$I_t = 0$	200	400	600	800
	0	0.74	0.09	0.07	0.06	0.05	0.73	0.08	0.07	0.06	0.05
	200	0.17	0.48	0.17	0.10	0.09	0.26	0.49	0.10	0.08	0.07
I_{t-1}	400	0.19	0.09	0.55	0.09	0.07	0.16	0.19	0.43	0.12	0.10
	600	0.09	0.11	0.15	0.49	0.16	0.11	0.13	0.16	0.44	0.16
	800	0.07	0.08	0.10	0.13	0.61	0.09	0.10	0.11	0.13	0.57

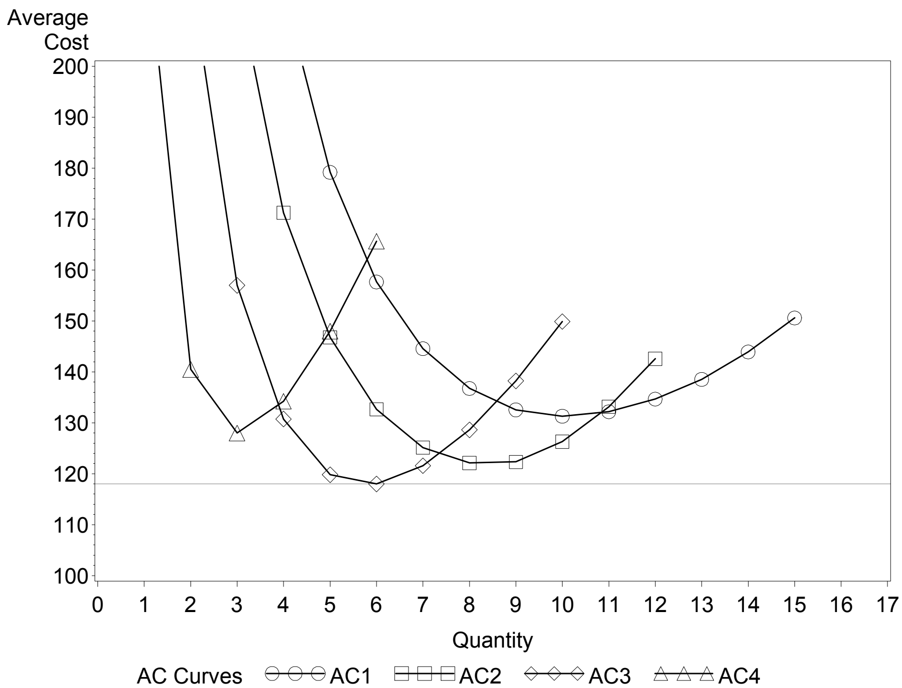

Figure 1: Average cost curves for UNQ treatment

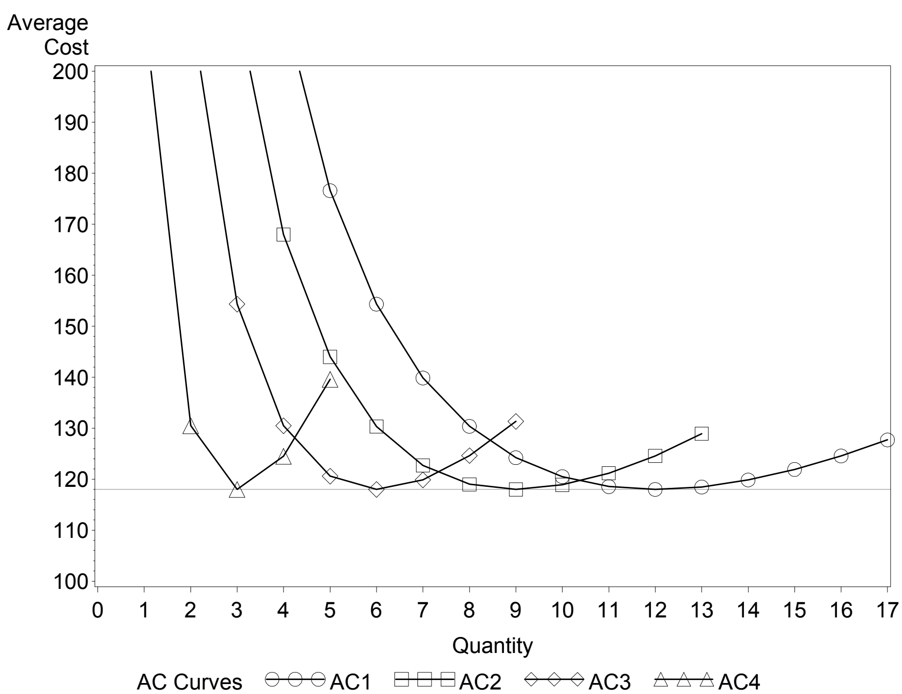

Figure 2: Average cost curves for CRS treatment

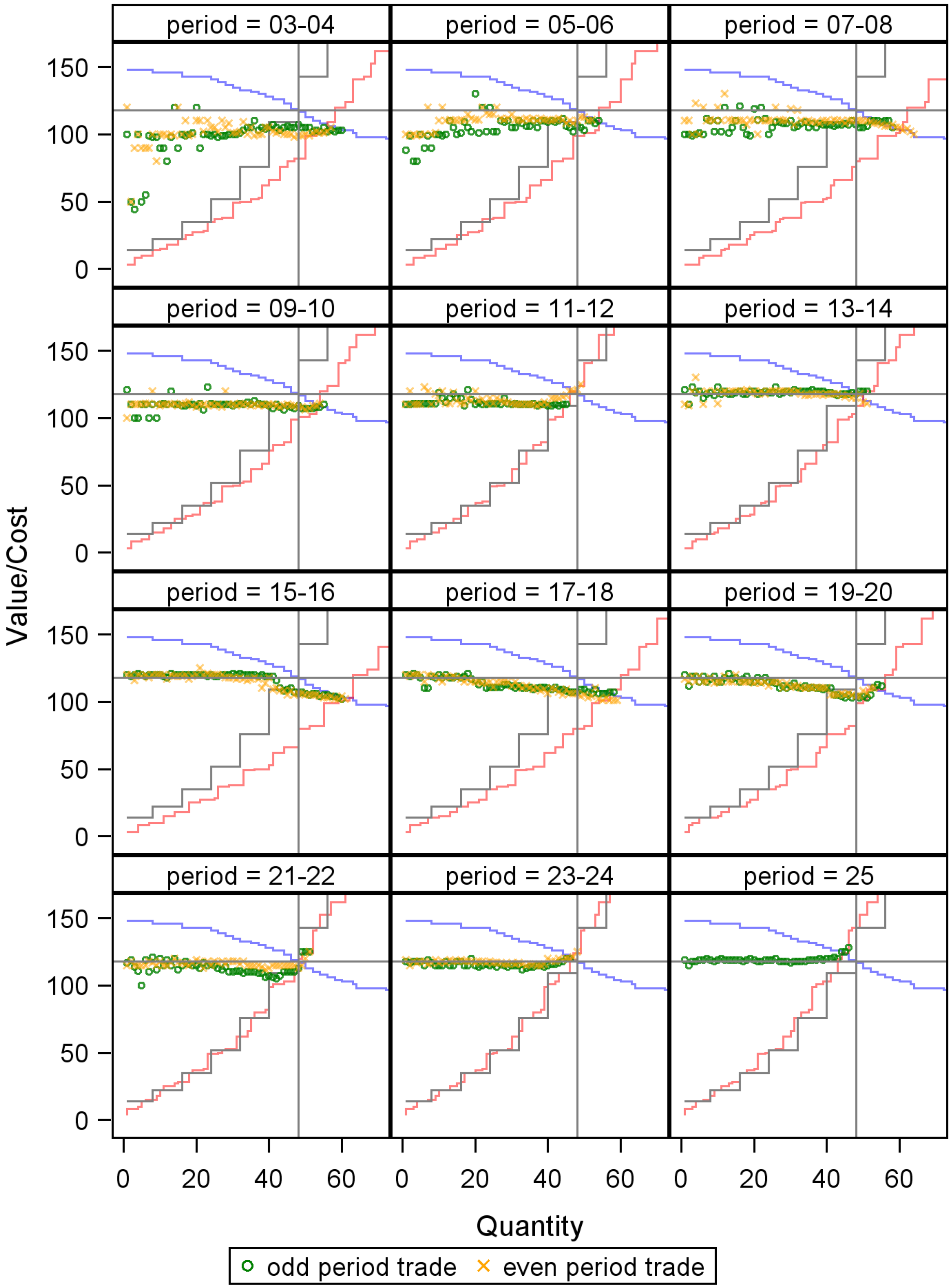

Figure 3: Demand, realized short run supply, and trades in the UNQ08 session

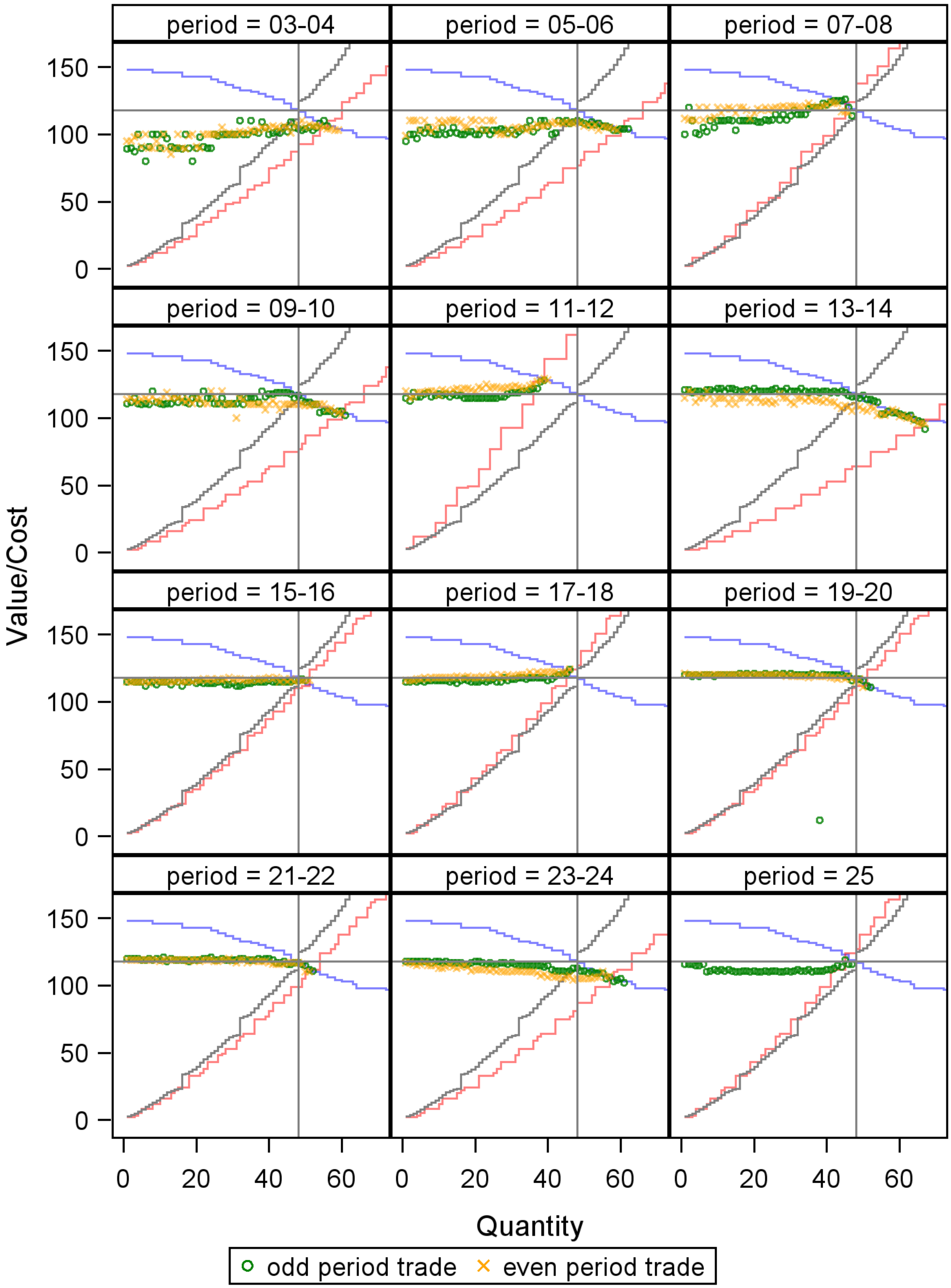

Figure 4: Demand, realized short run supply, and trades in the CRS02 session

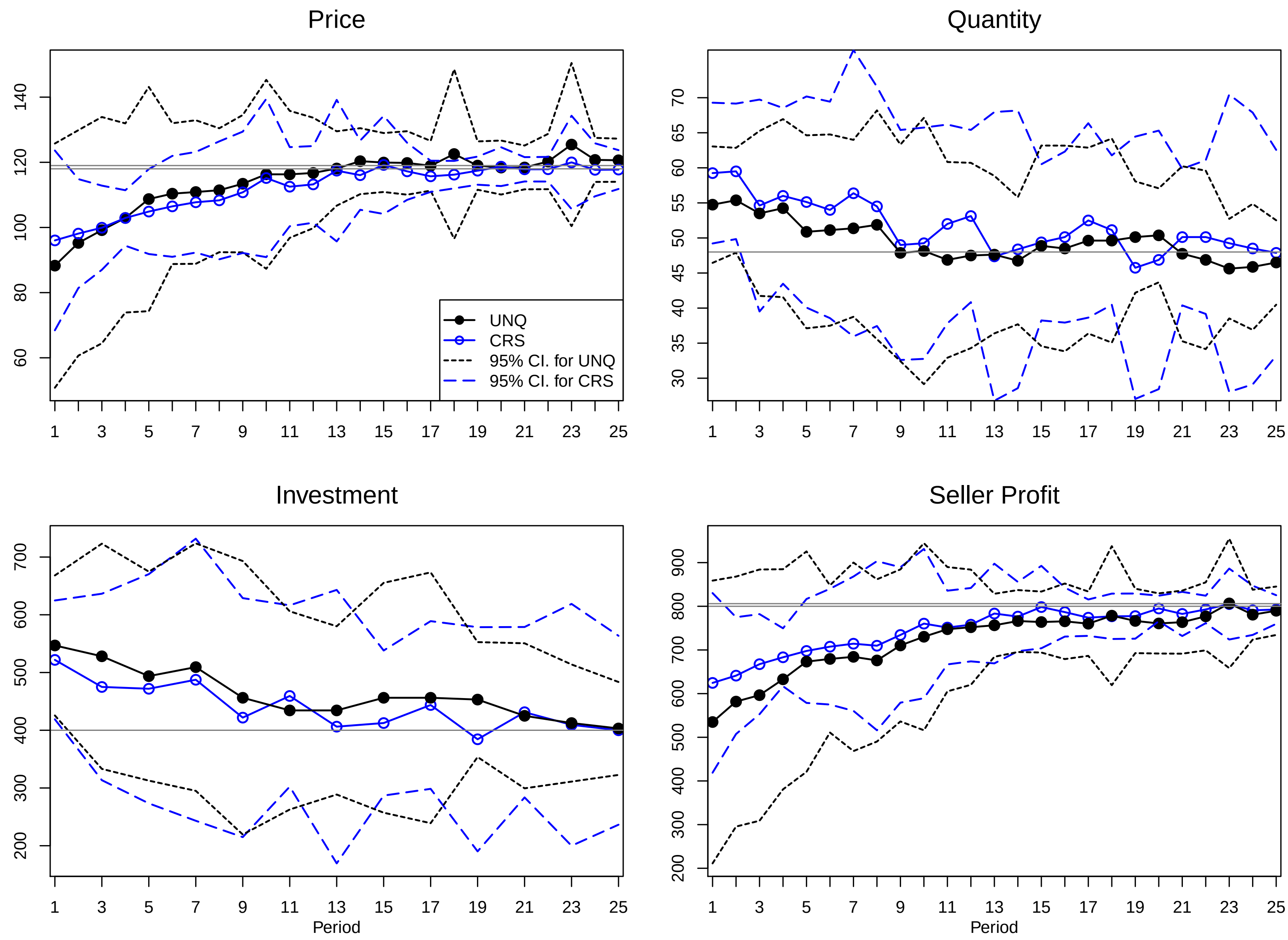

Figure 5: Time series of average price, quantity, investment, and seller profit

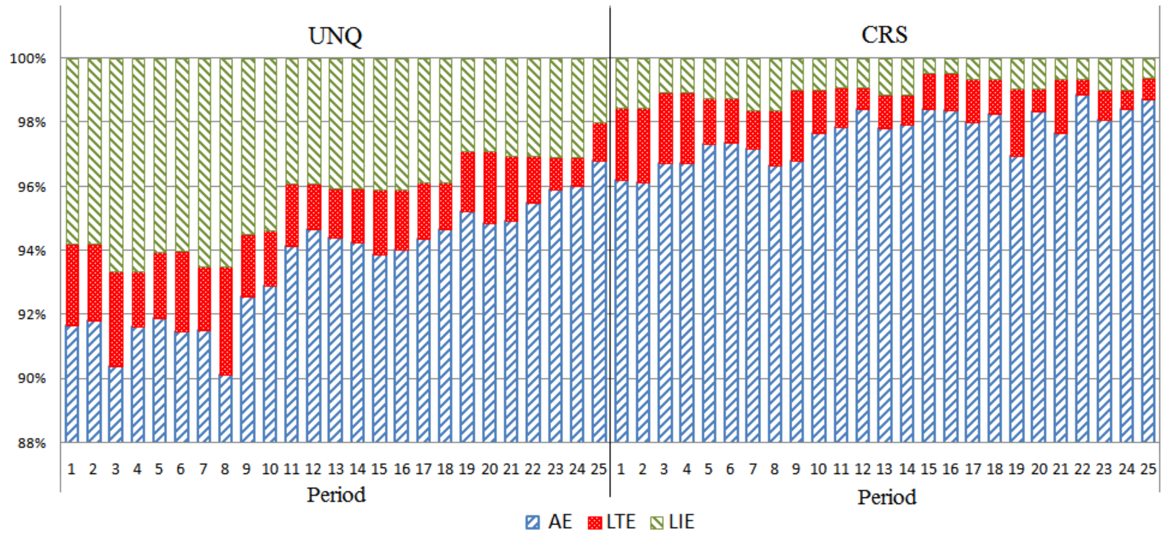

Figure 6: Allocative efficiency decomposition for each period

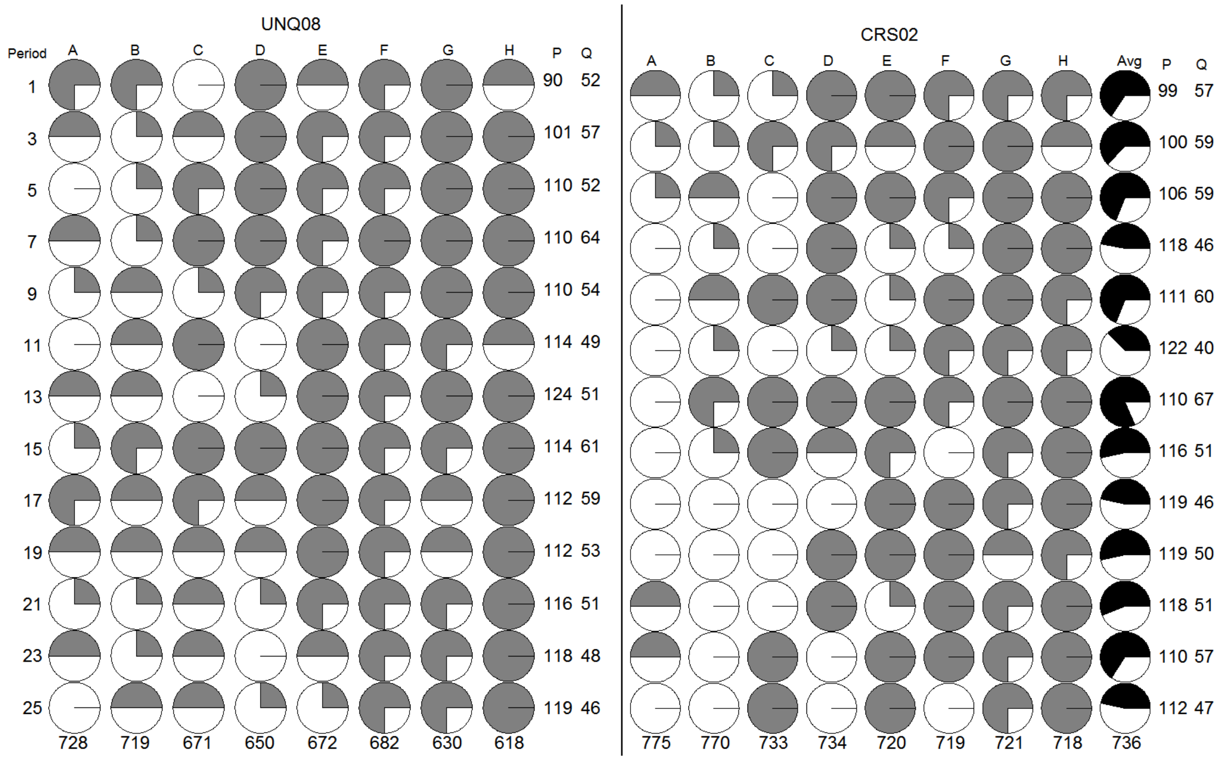

Figure 7: Individual investment choices in sessions UNQ08 and CRS02

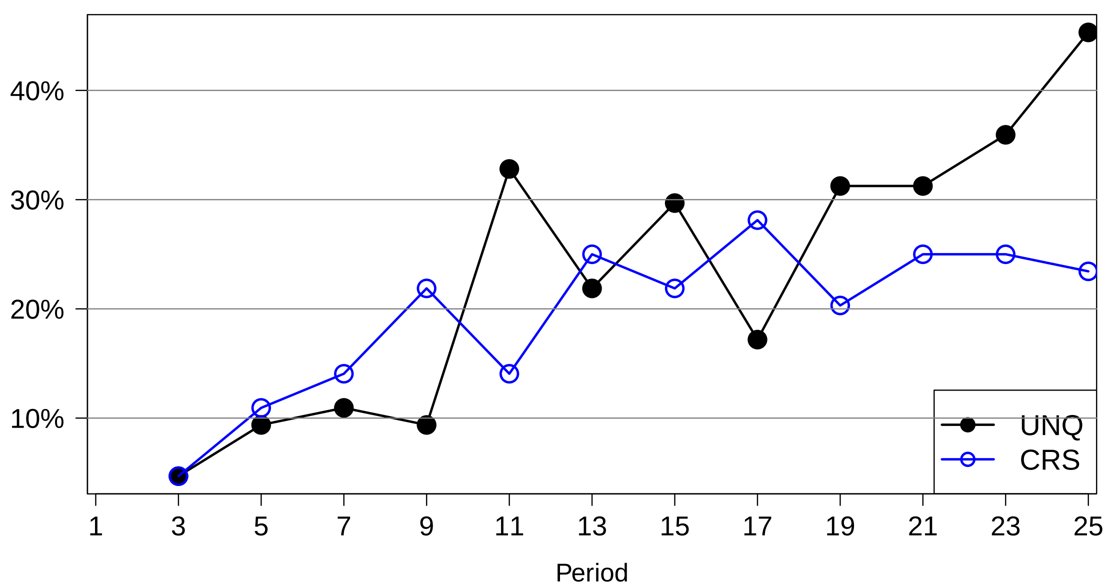

Figure 8: Proportion of best response investment decisions in each period.

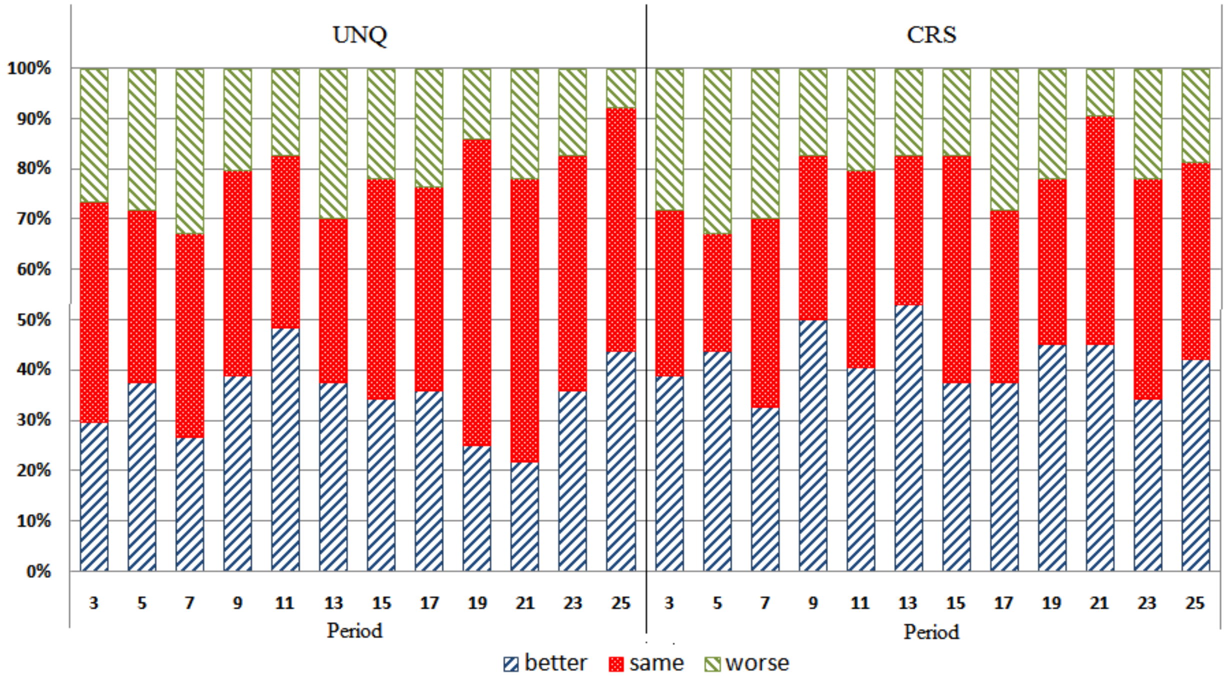

Figure 9: Proportions of better, same, and worse investment transitions

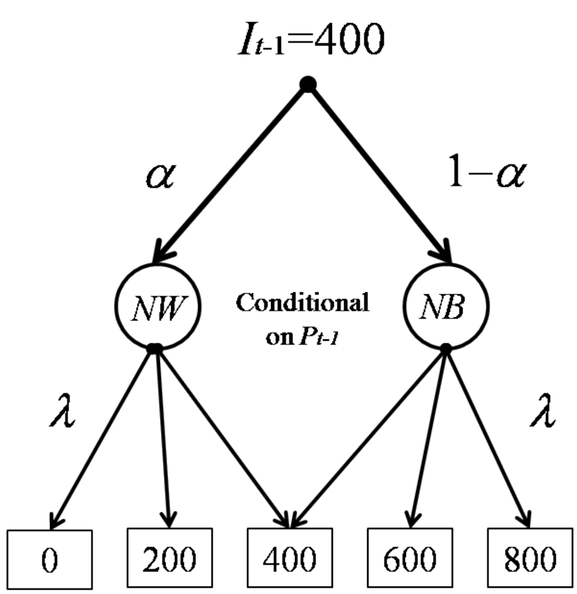

Figure 10: An example of the two stage determination of investment transition probability

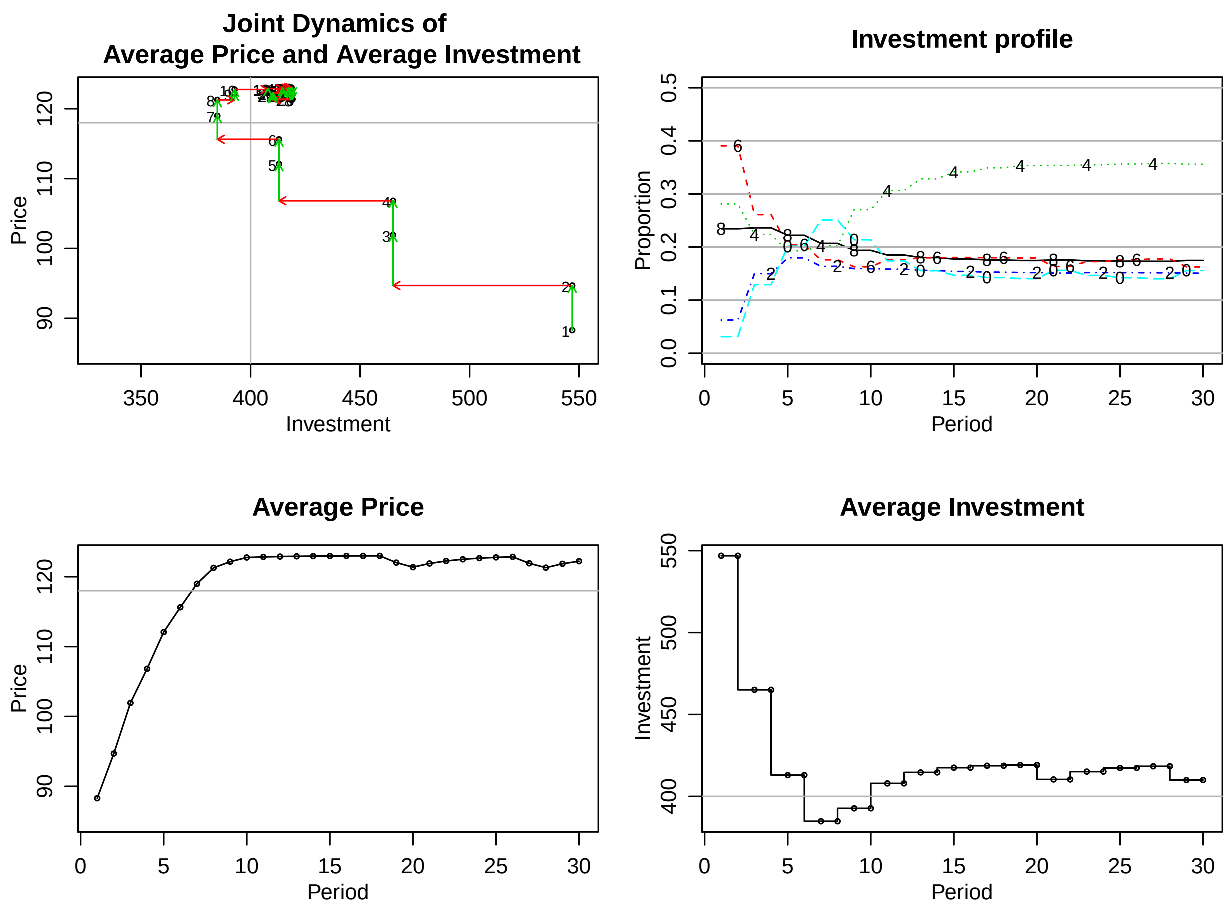

Figure 11: Expected dynamics under estimated model - UNQ treatment

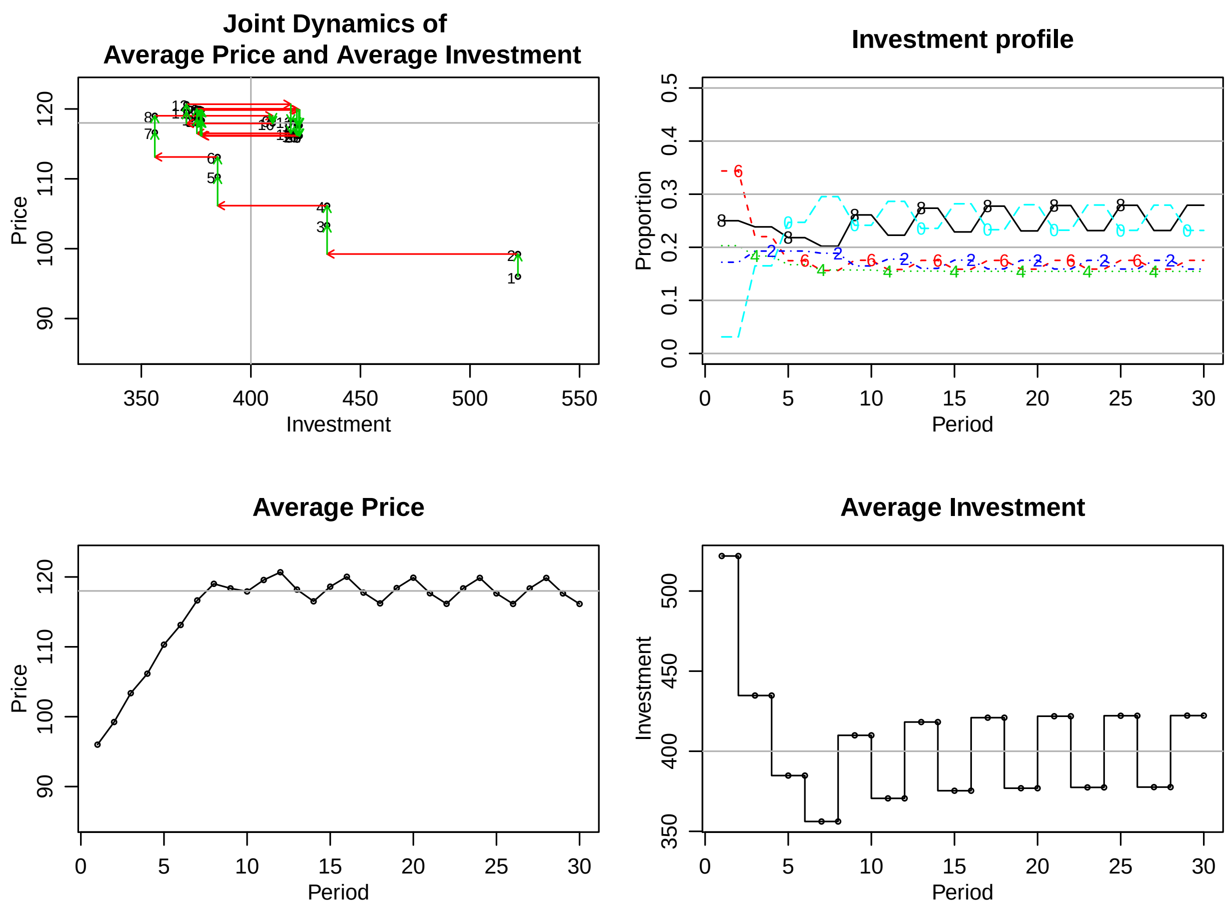

Figure 12: Expected dynamics under estimated model - CRS treatment