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

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

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**Abstract**

We report on an experiment investigating whether the Hayak 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 common constant returns to scale technology having 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. We show that price formation is adaptive and quickly converges to realized short run equilibrium, but long run investment decisions exhibit very limited rationality. We present and estimate an investment choice model that shows that only minimal rationality, coupled with repeated decisions, is enough to achieve high long run allocative efficiency when markets use continuous double auctions.

*JEL classification:* C92; D02

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

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# 1 Introduction

How should society allocate productive inputs to different goods markets? Solutions to this problem need to accommodate that, for many goods, the levels of some inputs must be set well in advance of final production and consumption. In such circumstances, this question takes the form of how should society allocate productive resources amongst various industries, and at more granular level, what should be the number and scale of firms within such industries? When called upon for answers to these questions, the economics community typically advocates policies that facilitate competitive and free markets. This support 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) famous conjecture that unfettered markets *implement* competitive equilibrium prices and allocations when consumers' and firms' information is decentralized and private.

Despite this unequivocal prescription of pursuing free markets, some of the most (perceived to be) ardent capitalistic societies routinely adopt market-distorting industrial policies. In the United States some examples of such market interventions are the actions of the Small to Medium Business Administration, various federal energy policy acts from 2005 to 2008, and the high profile bailout of three major automobile manufacturers in 2009; the Chinese 5 Year Plans are a series of broadly based industrial policy measures; and within the last decade Singapore authorities have used government policies and resources in attempts to establish a biotechnology sector and then a casino integrated resort industry within the island state. With some of the most market oriented and successful economies pursuing aggressive market intervening policies, has the economics community gotten it wrong?

In this study, we experimentally test the conjecture that a competitive market solution arises and solves this resource allocation problem in simple market settings. We consider settings in which a buyer only knows her own valuations for a commodity and a seller only knows his own opportunity costs for selecting the scale of his firm in the long run and the corresponding possible short run marginal costs of production. Our study is a natural attempt to extend the applicability of perhaps the most significant finding in experimental economics. Smith (1962) first coupled this decentralized private information setting, excluding the long run scale decision of the sellers, with a continuous double auction trading institution and found the implementation of the competitive equilibrium extremely robust. After 20 years of subsequent research on the double auction, Smith (1982) synthesized this research and provided a strong affirmation of what he coined the "Hayek Hypothesis." A half century after the first publication of Smith's experimental results, the reliability of the Hayek hypothesis is so strong that classroom replications of Smith's test of the Hayek hypothesis are now a common activity in modern economics curriculum.

When extending from the short to the long run, the competitive equilibrium market clearing condition also extends 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 of entering firms. 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 a constant returns to scale represented by a constant long run average cost function. We parameterize these technologies and pair them with a constant market demand curve such that the long run equilibrium (LRE hereafter) market price and quantity coincide. However, the different technologies affect the determinacy of the LRE in terms of the scale and number of firms. With the U-shaped average cost curve technology the LRE is unique and all firms choose the level of fixed input that minimizes the average cost - consequently we call this our UNQ treatment. In contrast, with constant returns to scale there is a multiplicity of LRE in terms of the number of sellers and their firms sizes as defined by the choice of fixed input - we call this the CRS treatment. We view the UNQ treatment as giving the Hayek Hypothesis the best chance to hold, and the CRS treatment as a greater stress test.

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 trading efficiency in UNQ treatment.

The convergence to the LRE is slower than what others typically observed; 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 supply conditions and tracks the short-run partial equilibrium as in previous studies. The main source of the sluggish convergence is the low levels of rationality and slow adjustment of seller's long run investment decisions.

Sellers' investment choices coincide too little with the best responses to past prices to be reasonably modeled by random utility based equilibrium (Mckelvey and Palfrey, 1995) or adjustment (Camerer and Ho, 1999) models. The only rationality we find is a slightly higher probability to move from the current investment level to investment levels as least as profitable than to move to investment levels no more profitable - with a significant inertia not to change investment levels. 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. 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 robustly generates highly efficient outcomes.

The ability of double auctions to robustly generate high allocative efficiency, has lead many (Easley and Ledyard, 1993; Gjerstad and Dickhaut, 1998; Asparouhova, Bossaerts, and Ledyard, 2011) to model what type of behavior leads to this result. In particular Gode and Sunder (1993) show that if buyers and sellers use zero intelligence strategies, a buyer makes random bids below her unit value and a seller makes random asks above his unit cost, final allocations are likely to maximize allocative efficiency. Our results for the long run show that an even less rational rule for investment decisions - sellers randomly choose investment levels that are only more likely to be in their better than set - leads to high allocative efficiency. In terms of market design problems, we think the identification of trading institutions and market environments that robustly generate desirable sets of allocations under a wide set of behavioral rules is an important advancement.

Our results also contribute previous experimental double auction market studies considering the issue of production technology and timing. These studies have primarily focused on production in advance. In a variation of Smith's basic design, a string of studies considered the impact of requiring sellers to commit to production levels before the output market takes place. The first studies (Mestelman and Welland, 1987; Mestelman, 1988) considered the perishable good case (no inventory carryover) and found market quantity and price fell below the competitive equilibrium levels. Subsequent studies (Mestelman and Welland, 1991, 1995) allowing inventory carrying over reduced, but not eliminated, these shortfalls.[1] Other studies incorporate full general equilibrium production economies with endogenous determination of input prices and allocations; for example Riedl and van Winden (2007), Riedl and van Winden (2012), Noussair, Plott, and Riezman (2007), and Goodfellow and Plott (1990). However, these studies have uniformly chose to resolve reallocation by conducting input markets first, then production, and finally conducting output markets. These experimental economies are characterized by slow convergence to competitive equilibrium from below equilibrium input prices and production levels. Interestingly, these are all in contrast to our results in which equilibrium is achieved from over commitment to firm scale, over production of the output good, and below equilibrium output prices.

We proceed by presenting our experimental design and protocols. Then we analyze the

[1]Phillips, Menkhaus, and Krogmeier (2001) finds the overwhelming majority of seller subjects prefer produce-to-order rather than produce-in-advance when given the choice, and also find that same pattern of underproducing and lower output prices in pure production-in-advance markets.

data to test whether the implications of the LRE hold. After establishing convergence to the LRE in both of our treatments, we study price dynamics and how economic information is aggregated in prices. Subsequently we document the limited rationality found in sellers' long run investment choices and present a Markov model of boundedly rational choice. Finally, we examine how the joint dynamics of investment and price leads to the LRE.

# 2 Experimental design

## 2.1 Economic Environment

Consider a sequence of twenty-five markets for a non-durable discrete good we benignly label "box". We often refer to an element of this sequence as a market period, or simply period. 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. Hence, our consideration is for the partial equilibrium of the box market.

In this situation 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.[2] Leased units of the fixed input generate a stream of revenue each period we call a 'profit bonus.' A seller's fixed cost is the opportunity cost of the units of fixed input he allocates to the

[2]Note, he can't rent from this market to increase his stock of the fixed input.

production of boxes. Explicitly, his fixed cost in 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. Accordingly 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* 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 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. Note that cost schedule #5 coincides with exiting the market: the investment level 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. In this figure, we observe that a seller's 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 and is presented in Panel B of Table 1. As in our UNQ treatment there are four alternative short run fixed/marginal cost pair schedules, with cost schedule #5 corresponding to an exit from the market. The plot of the CRS family of short run average total cost curves is presented in Figure 2. 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 will be 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 buyers' individual demands. Each buyer's demand in a given period is represented by a schedule of unit valuations. Table 2 gives the eight individual demand schedules used in our experiment, which we shuffle each period for the buyers. Thus, while subjects observes their own individual demand schedules changing, the market demand remains constant. The market demand curve is depicted in Figure 3. We chose this particular market demand curve so that at the price of 118 the market quantity demanded is 48. This allows for crisp definition of the LRE.

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. In addition to the short run market clearing condition, at a LRE price no seller would be better off by changing their investment level. This condition implies that price is at least as large as the minimum of the LRAC and also smaller than the price that would make it more profitable for a seller to increase his investment; in our experiment this is the interval [118,119]. 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). In our environment, this corresponds to every seller earning nominal profit in the range [800,806] each period. The LRE of the UNQ and CRS treatments differ in the fourth condition concerning the investment profile. For the UNQ treatment, the unique investment profile has every seller invest 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.

## 2.2 Institution

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.

The second component is the subjects' participation in the computerized double auction that permits trading between buyers and sellers in each of the twenty-five market periods. The double auction has a length of 165 seconds. During the double auction buyers and sellers can freely submit public - but anonymous - price proposals. We call a buyer's price proposal a bid, and this is a public message indicating a price at which the buyer is willing to purchase a single box. All successfully submitted and active bids are placed in a publicly observable bid queue that is displayed on every subject's computer monitor. In addition, each buyer's monitor displays another list consisting only of her own bids. The only rule governing the submission of bids is that a new limit bid must strictly exceed any bid in the queue. We call a seller's price proposal an ask, and this is a public message indicating a price at which the seller is willing to sell a single box. All successfully submitted and active asks are placed in a publicly observable ask queue that is displayed on every subject's computer monitor. In addition, each seller's monitor displays another list consisting solely of his own asks. The only rule governing the submission of asks is that a new limit ask must be strictly lower than any ask in the ask queue. A buyer (seller) is free to remove one of her bids (his asks) as long as it is not the highest (lowest) in the queue.

A trade can occur two ways. (1) A seller submits an ask that is smaller than the current highest bid in the bid queue, resulting in the seller and the buyer with the highest bid transacting for one box at the buyer's bid price. In this case the bid is no longer active and removed from the bid queue - and the seller's ask is never placed in the ask queue. (2) A buyer submits a bid exceeding the lowest active ask, generating a trade of one box at the ask price between the buyer and the seller who submitted the lowest ask price. In this case the seller's ask is no longer active and removed from the ask queue and the buyer's bid is never placed in the bid queue. 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. A buyer can keep track of her current period accrual of earnings by inspecting a region of her computer interface called the "Trade Summary." This is a table whose columns correspond to the sequence of boxes that she can buy. The rows correspond to the unit valuation of the box, the price paid, the unit profit, and the cumulative period profit. 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. A seller can keep track of his accumulated earnings within a period by inspecting his trade summary which is the same as the buyer one except for an appended column giving the period profit bonus to start the table, and appropriately replacing the row of unit value with unit cost. Earnings for each period and cumulative earnings for all completed periods are also readily available via the experimental software. At the conclusion of the experiments, a buyer's and a seller's earnings were converted to the local currency Chinese Yuan at an exchange rate of 50 to 1 and 1000 to 3, respectively.[3]

## 2.3 Experimental Protocols

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. The ranges and standard deviations of subject payments by role and treatment are reported in Table 3. The variation of payments to buyers are much larger than that to sellers because of disequilibrium outcomes in which consumer surplus exceeds, and producer surplus fails to meet, LRE levels.

The following protocol is used to conduct every session. FEEL uses the ORSEE Online Recruitment System (Greiner, 2004) for subject recruitment, which at the time of the experiment contained approximately 1200 Xiamen University 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. 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[4] that the subjects read individually.[5] 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.

[3]The exchange rates are chosen so that, in equilibrium, the buyer's and seller's expected earning in Chinese Yuan were the same.

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

[5]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.

# 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 theoretical benchmarks. Figure 4 is this visualization for our UNQ treatment session UNQ08, and is a $4 \times 3$ array of data plots. Each plot consists of the data from pairs of market periods that proceed 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 darker open circles, and (3) the transaction price sequence of the second market period denoted by the lighter open circles. This session is typical[6] 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 5 provides the same data visualization for CRS treatment session CRS02. One difference in this figure is the equilibrium benchmark short run supply schedule. For the CRS treatment there are 33 different combinations of investment levels, and corresponding chosen cost schedules, with the average level of investment 400. All of them are possible long run equilibriums. The short run market supply is different for each combination, although

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

the market quantity supplied is 48 at the price of 118 for each combination. To generate the benchmark inverse short run supply schedule we take the average unit costs of the 33 equilibrium investment profiles for each level of output. In this figure we again note that within market periods 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

Our foremost question is whether the robustness of the Hayek hypothesis extends to the long run. We now address this question by comparing the values of various economic variables in our experiment versus their respective theoretical predictions. The key variables we consider are price, market quantity, market level investment, seller's profits, and allocative efficiency. In Table 4 we report the means of these variables for the first and second halves of the experiment, periods 1-12 and 13-25 respectively. Then, in Figure 6, we provide a more detailed time series comparison of 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 6, 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 quantity falls in line with the observed prices. In the 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 6.

Now let's take a first coarse look at the seller's investment decisions and profits. We consider average investment levels[7] in Table 4 and Figure 6 where we see that in both treatments there is early over investment that slowly declines to the LRE average level of 400. These slow adjustments in investment are surprising as we have seen price adjusts quite quickly to the short run levels. Further, we can 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 they could realize in experimental currency. 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 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 coordinate on efficient investment levels. Previous experimental studies only concerned the first factor. To measure the effect of these factors we develop a decomposition of the allocative efficiency and efficiency losses attributable to these two factors. 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.

[7] Considering the average is a somewhat erroneous simplified measure in the UNQ case, and later we consider the whole investment profile.

Maximum potential gains, $MLR$, is similarly calculated as the sellers' and buyers' market earnings and the sum of the sellers' profit bonuses in the LRE. Now define $MSR$ as the maximum possible gains given the seller's investment profile. The ratio of $RG$ to $MSR$ is the allocative efficiency measure often reported in experimental studies of short run markets. By definition,

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

Call the two right hand terms trading efficiency,$TE$, and investment efficiency, $IE$, respectively. Further denote the efficiency loss for each respective measure as $l_{AE}, l_{TE}$, and $l_{IE}$. We establish a decomposition of the the loss in overall efficiency as follows.

$$\begin{aligned} AE = TE \cdot IE &= (1 - l_{TE}) \cdot (1 - l_{IE}) \\ &= 1 - l_{TE} - l_{IE} + l_{TE} \cdot l_{IE} \\ &\approx 1 - l_{TE} - l_{IE}, \end{aligned}$$

or

$$l_{TE} + l_{IE} + AE \approx 1.$$

For each treatment, we calculate the average of the three terms for each market period across the 8 sessions. These results are plotted in Figure 7.[8] 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 high performance of double auction mechanism in realizing exchange gains in short run markets - as is

[8] The term we drop from the approximation has little impact in almost all periods because both $l_{TE}$ and $l_{IE}$ are less than 5%, so the product of them is no more than 0.25%.

consistently observed in the literature.

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?

# 4 Price and Investment Dynamics

Price and investment are the two key endogenous variables in our experimental market. In this section we present and estimate models of the dynamics of both variables. Then we put the estimated pricing and investment profile models together to demonstrate that markets converge to the LRE despite of low levels of observed rationality.

## 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:

$$\bar{P}_{s,t} \quad = \quad \beta_s + \beta_1 \bar{P}_{s,t-1} + \beta_2 \bar{I}_{s,t} + u_{s,t}$$

in which $\bar{P}_{s,t}$ is the average trading price in period $t$ of session $s$, and $\bar{I}_{s,t}$ is the average investment. The random effects estimation of this model for our two treatments is reported in Table 5. We see the coefficients of both the previous price and the current investment level are significant, and the estimated models explain about 76% (UNQ) and 73% (CRS) of variation in average prices.

Each of the estimated regression equations describes a price process having an investment level conditional equilibrium price of, $P^e|\bar{I} = \frac{\beta_0}{(1-\beta_1)} + \frac{\beta_2}{(1-\beta_1)} * \bar{I}$. In Figure 8, we compare these estimated relationships to the underlying short run equilibrium relationship defined by the experimental parameters. It is clear that this estimated equilibrium relationship and the theoretical short run equilibrium relationship coincide in the ranges of average investment we observe.[9]

Another implication of the regression results is 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 $\beta_1 > 0$. Even if investment profiles are constant across periods, we can only expect geometric convergence to equilibrium prices. This suggests that while the Hayek Hypothesis holds well for these short run comparative statics, market prices don't instantaneously adjust to a new short run equilibrium. This begs the question how do prices incorporate information regarding changing investment profiles as the Hayek hypothesis predicts?

Now we examine the transaction level data to investigate how information about short run supply is aggregated by price. Recall that Figures 4 and 5 provide much of this transaction level data and can provide suggestions to these driving forces. One feature of this data is that prices within early periods start low and increase toward short run equilibrium levels as the period end approaches. A second feature, at some point in the session the sequence of prices closely follow a constant level until one of two events occurs. One event is when the prevailing price is below the market clearing level, and the supply of boxes

[9]Our analysis here relies strongly upon buyers and sellers acting "as if" they are price takers and quantity traded is fully identified by the market clearing condition. This assumption could prove erroneous if either buyers or seller's exercise market power by withholding units from the markets; however, studies such as Holt, Langan, and Villamil (1986); Davis and Williams (1991); Fehr and Falk (1999) have studied this question in various contexts and find that in double auction markets this is only the case when a party holds very strong market power and is experienced.

exhausts before demand. During the subsequent shortage, transaction prices rise following the supply schedule until no more (or minimal) shortage remains. And the second event is when the price level exceeds the short run equilibrium price, and the demand for boxes exhausts before supply. During this surplus, transaction prices trend downward following the demand schedule until no more (or minimal) surplus remains. A consequence of the price adjustments to surpluses and shortages, the closing prices in odd periods, i.e. those following new investment choices, provide meaningful information about market conditions and the corresponding market clearing price. The third feature is this odd period closing price information does not fully get incorporated into the prices of the subsequent period. Rather the subsequent opening price returns close to the previous opening price. Consequently, while the price adjustments to late period surpluses and shortages are information flows that facilitate the Hayek hypothesis, it appears that this information is only partially retained by subjects as they progress to the next period.

We investigate these factors through the following specification for the change in transaction price,

$$\begin{aligned}\Delta P_{s,t,j} = \alpha_{s,t} \quad &+ \quad \beta_1 D_{shortage}(h_{s,t,j}, P_{s,t,j-1}) * (\underline{C}(h_{s,t,j}) - P_{s,t,j-1}) \\ &+ \quad \beta_2 D_{surplus}(h_{s,t,j}, P_{s,t,j-1}) * (P_{s,t,j-1} - \overline{V}(h_{s,t,j})) \\ &+ \quad (\beta_3 + \beta_4 D_{\{t \text{ is odd}\}})(P^C_{s,t-1} - P_{s,t,j-1}) + \varepsilon_{s,t,j}\end{aligned}$$

The dependent variable, $\Delta P_{s,t,j}$, is the change in price of the number $j-1$ to the number $j$ unit traded in period $t$ of session $s$. Let the market state, $h_{s,t,j}$, be the collection of the array of remaining market unit valuations - the remaining demand - and the array of remaining market unit costs - the remaining supply - after the first $j-1$ trades of period $t$ in session $s$. The function $\underline{C}(h_{s,t,j})$ returns the minimum of the remaining units costs for the market state, and its value is infinite when there is no remaining supply. Likewise, the function $\overline{V}(h_{s,t,j})$ selects the maximum of the remaining unit valuations for the market state, and is zero if there is no remaining demand. The dummy variables $D_{shortage}(h_{s,t,j}, P_{s,t,j-1})$ and $D_{surplus}(h_{s,t,j}, P_{s,t,j-1})$ are indicator functions for whether the market is currently in shortage and surplus respectively. The dummy variable $D_{\{t \text{ is odd}\}}$ is a indicator function for when $t$ is an odd numbered trading period. Finally, the closing price of the previous period is denoted $P^C_{s,t-1}$.

Let's consider the coefficients in this model. When the market is in a shortage, price should rise enough that the remaining unit with lowest cost can be sold profitably. This suggests $\beta_1$ should be at least one. Correspondingly when the market is in surplus, price should fall enough that is less than the highest remaining unit value in order for the buyer associated that unit can purchase at a gain. This suggests $\beta_2$ should be less than negative one. Parameter $\beta_3$ measures the impact previous closing price has on expectations and price formation. We should expect the value of this parameter to be in the unit interval, and close to one if traders fully incorporate the information revealed by closing prices. However, since only the closing price of odd numbered periods is informative, the closing price of even numbered periods should not provide an anchor in the subsequent period. This implies that $\beta_4$ should be the negative of $\beta_3$.

We estimate this model with the panel data set of each treatment; one dimension is the sequence of trades within the period, and the other dimension is the periods of each session. In Table 6 we report the parameter estimates of the panel regression with random effects specification controlling for inter-period and inter-session heterogeneities.[10] For both treatments we find significantly positive estimates of $\beta_1$ implying that price will increase when there is a shortage. In the CRS treatment $\beta_1$ is greater than one making it large enough to render the first extramarginal unit of supply profitable. However, in the UNQ treatment $\beta_1$ is less than one suggesting when there is a shortage the seller holding the first extramarginal unit of supply sells it at a loss. This is confirmed to have happened a number of times in the data, and we are at a lost for a reason why. When the market is in

[10] We conducted a Hausman test with random effects as the null and fixed effects as the alternative. The $p$-value of this test are 0.050 and 0.273 for the UNQ and CRS treatment respectively.

a surplus state, and estimated values of of $\beta_2$ are less than negative one for both treatments implying that price will decrease enough to switch the first extramarginal unit of demand to intermarginal.

The estimates of $\beta_3$ and $\beta_4$ reveal aspects of how market price absorbs information about the state of short run supply. First, $\beta_3$ is significant but less than one, indicating that information provided by closing prices in odd periods is only partially incorporated by the prices of the subsequent even period. Second, $\beta_4$ is not significant indicating that the effect on the closing price of an even period is the same as that of an odd period despite the fact there is almost always going to be a shock to the short run supply curve and sellers should anticipate this. All told, transaction level prices adjust in the presence of shortages and surpluses as one would expect in a price taking model. However, the information content of the resulting prices is only partially carried across market periods.

## 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 9. 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 period 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 the average price, rounded to the nearest integer, and market quantity of boxes sold in the subsequent even-numbered period (except for period 25, the last trading period, for which the average price and quantity is for that period it self). The bottom row gives the average period total earnings for each seller.

Figure 9 exhibits several features that suggest many investment choices are not optimal. First it is clear than when prices are below the LRE level of 118 most sellers do not exit the market. Second, in the UNQ session, even after the price is around the LRE level only a minority of the sellers select the optimal investment level of 400. Third, when many individuals do adjust the investment level it is often the smallest possible adjustment size of plus or minus 200. There are a couple of exceptional individuals in the CRS session who seem to only switch between either exit or 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.

### 4.2.1 Rationality in investment choices

To assess the extent investment choices are optimal we first consider a best response benchmark. We define a seller's profit function $\pi(p, k)$ as the value of the solution to the seller's profit maximization problem assuming price $p$ conditional on investment level $k$. When evaluating the profits of alternative investment levels we assume a seller's price expectation is adaptive and $p$ is the average previous period price[11]. Figure 10 plots this profit for each of the five investment levels for varying level of prices. For the CRS treatment, we can see for prices strictly below 118 that exiting the market is best response and that ranking of the profit levels is strictly decreasing in investment level; for prices strictly above 118 the maximum investment of 800 is the best response and the ranking in now strictly increasing in investment level; and at price equal to 118 profit is constant across investment levels. Things are more complicated for the UNQ treatment, the best response goes from exiting

[11]Unreported analysis shows there is little difference in our results if we set the expectation of price as the average of the previous two period prices, the previous closing price, or we assume sellers are forward looking with rational expectation and set $p$ equal to the average price of the subsequent period.

the market when price is below 118 to investing 400 for the range of prices we observe in our experiment that exceed 118. However, the ranking of the profit levels is not monotonic and switches of rank occur at various prices.

For each investment task starting from period 3, we calculate the proportion of sellers' investment choices that are a best response to the previous period average price. We report the time series of this proportion for each treatment in Figure 11. This figure indicates that there is, at best, very low levels of best response behavior. 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 poor 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 the choice of current investment relative to the previous investment level, and simply ask whether sellers are more likely to transit to an investment level offering greater profit than to one offering lower profit. For the current level of investment and realized average price we consider three type of investment transitions: a 'better' investment transition is a switch to one that offers 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 level; and a 'worse' investment transition is to one that offers a strictly lower profit. In Figure 12 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. The model assumes that the dynamics of a subject's investment choice follows a first order Markov process. The transition probabilities from the previous investment level to the five possible levels depends upon two factors; first, the probabilistic tendencies to move to a investment level in the set offering profits as least as high as opposed to the tendency to move to a level in the set offering no better profits; and second, there is a bias for transitions to closer rather than farther investment levels. After formulating a two parameter model capturing these two factors, we estimate the parameter values and explore the limiting distribution, i.e. equilibrium, of this process.

A two stage process determines the transition probabilities from the previous investment level, given the average price of the last even numbered period, $p_{t-1}$, to the current investment choice. In the first stage, probability is allocated to two subsets of possible investment levels. The two sets are the subset of investment levels that are not worse - $NW$ - than the previous investment level $I_{t-1} = k$ and the subset of investment levels not better - $NB$ - than $I_{t-1} = k$;

$$\begin{aligned} NW(p_{t-1}, k) =& \{j \in \{0, 200, 400, 600, 800\} : \pi(p_{t-1}, j) \geq \pi(p_{t-1}, k)\}, \text{ and} \\ NB(p_{t-1}, k) =& \{j \in \{0, 200, 400, 600, 800\} : \pi(p_{t-1}, j) \leq \pi(p_{t-1}, k)\}. \end{aligned}$$

Note that $NW$ and $NB$ are not exclusive as they will share at least the previous investment level as a common element. We assume that an $\alpha$ 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 allowing for the possibility that sellers favor moving to investment levels that are closer rather than farther from the current level. Specifically probability is allocated according to the number of steps between an element and the previous investment level.

The step count between investment levels $j$ and $k$, is

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

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 $\lambda$ 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;

$$\begin{aligned}\Pr(I_t = j|I_{t-1} = k) =& X_{(j \in NW(p_{t-1},k))} * w(I_t = j|I_{t-1} = k, NW(p_{t-1}, k), \lambda) * \alpha + \\ & X_{(j \in NB(p_{t-1},k))} * w(I_t = j|I_{t-1} = k, NB(p_{t-1}, k, \lambda)) * (1-\alpha),\end{aligned}$$

where $X_e$ is an indicator function for set $e$. 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 $\lambda$.

Consider an example with the CRS treatment. Suppose the previous price is strictly less than 118, and the previous investment level is 400. Figure 13 shows schematically the two stage process. In the example $NW = \{0, 200, 400\}$ and $NB = \{400, 600, 800\}$, and probability $\alpha$ and $1-\alpha$ is assigned to each respective set. Then each set's probability is allocated to its elements as determined by $\lambda$. Table 7 gives the full transition probability matrix $\Pi(p; \alpha, \lambda)$ 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 8. The two estimates of $\alpha$ 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 $\lambda$ 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. $\lambda \neq 0$.

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 9 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.

Holding price constant, we can examine the limiting distribution of the Markov transition matrix. This limiting distribution reflects the proportion of time a seller will spend at each investment level, and with a large number of sellers this would be the expected proportion choosing each investment level in a market period. In Figure 14 we plot the average investment levels of these limiting distribution for each treatment at varying price levels. For price below 118, the Markov matrix is constant for CRS treatment. In this case the average investment of the limiting distribution is around 320, which is well above the rational level of 0. Likewise, for prices above 118 the average investment of the limiting distribution is around 480, well below the profit maximizing level of 800. The average investment-price equilibrium correspondence for the UNQ treatment is more complicated because the ranking of alternative investment levels by profit change more frequently and sometimes are non-monotonic. Still we can see that at the LRE price of 118 the average of the limiting distribution for the UNQ, and CRS, treatment is 400.

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 the average prices in period 2 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 40. In Figure 15, 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 an 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 15. 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 cylce 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 mimicing the dynamics of the experimental data as it converges to the LRE. Furthermore, it provides an demonstration of how a behavioral rule, which incoporates very minimal rationality, used in conjunction with the double auction trading institution robustly generates LRE outcomes even in the challenging multiple equilibrium case of CRS.

# 5 Discussion

We asked can economies in which markets have the typical defined long run and short run production horizons expect unfettered markets to 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); Cabrales and Serrano (2011); 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. Finally, we can look at the cases with production externalities, which is often the argument for distortional government policies.

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

Panel A: UNQ Treatment

| Cost Schedule # | Invest-ment | 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-ment | 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 | 97 |
| 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[b] | 120.19 | 106.34[b] | 117.62 |
| Quantity | 48 | 51.16[b] | 48.01 | 54.40[b] | 49.03 |
| Investment | 400 | 494.79[b] | 434.38[b] | 472.92[b] | 412.50 |
| Seller Profit | [800,806] | 665.93[b] | 771.99[b] | 704.13[b] | 787.06[b] |
| Allocative Efficiency | 100% | 92.18%[b] | 95.03%[b] | 97.11%[b] | 98.16%[b] |

[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.

[b] 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

| Variable | UNQ | CRS |
|---|---|---|
| Mean of $\beta_s$ | 53.51 (7.31) | 55.63(9.08) |
| $\bar{P}_{s,t-1}$ | 0.66 (12.06) | 0.64 (13.28) |
| $\bar{I}_{st}$ | -0.028 (-6.36) | -0.032(-7.11) |
| var($\beta_s$) | 14.59 | 14.98 |
| var($u_{s,t}$) | 27.12 | 17.95 |
| $R$-square | 0.761 | 0.731 |

The $t$-values of the parameter estimates are given in parentheses.

Table 6: Price dynamics within the period

| Variable | UNQ | CRS |
|---|---|---|
| Mean of $\alpha_{st}$ | 0.22 (1.68) | 0.13 (0.95) |
| $D_{shortage}(h_{stj}, P_{st,j-1}) * (\underline{C}(h_{stj}) - P_{stj-1})$ | 0.336(2.18) | 1.06 (7.30) |
| $D_{surplus}(h_{stj}, P_{st,j-1}) * (P_{stj-1} - \overline{V}(h_{stj}))$ | -1.29(-5.67) | -1.43(-3.30) |
| $(P^C_{s,t-1} - P_{st,j-1})$ | 0.19(-9.24) | 0.19(8.51) |
| $D_{\{t \text{ is odd}\}}(P^C_{s,t-1} - P_{st,j-1})$ | 0.00 (0.15) | 0.02 (0.66) |
| var($\alpha_{st}$) | 2.45 | 2.81 |
| var($\epsilon_{st}$) | 12.64 | 11.07 |
| $R$-square | 0.098 | 0.102 |

The $t$-values of the parameter estimates are given in parentheses.

Table 7: 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 | $\alpha + (1-\alpha)\frac{1^\lambda}{1^\lambda+2^\lambda+3^\lambda+4^\lambda+5^\lambda}$ | $(1-\alpha)\frac{2^\lambda}{1^\lambda+2^\lambda+3^\lambda+4^\lambda+5^\lambda}$ | $(1-\alpha)\frac{3^\lambda}{1^\lambda+2^\lambda+3^\lambda+4^\lambda+5^\lambda}$ | $(1-\alpha)\frac{4^\lambda}{1^\lambda+2^\lambda+3^\lambda+4^\lambda+5^\lambda}$ | $(1-\alpha)\frac{5^\lambda}{1^\lambda+2^\lambda+3^\lambda+4^\lambda+5^\lambda}$ |
| 200 | $\alpha\frac{2^\lambda}{1^\lambda+2^\lambda}$ | $\alpha\frac{1^\lambda}{1^\lambda+2^\lambda} + (1-\alpha)\frac{1^\lambda}{1^\lambda+2^\lambda+3^\lambda+4^\lambda}$ | $(1-\alpha)\frac{2^\lambda}{1^\lambda+2^\lambda+3^\lambda+4^\lambda}$ | $(1-\alpha)\frac{3^\lambda}{1^\lambda+2^\lambda+3^\lambda+4^\lambda}$ | $(1-\alpha)\frac{4^\lambda}{1^\lambda+2^\lambda+3^\lambda+4^\lambda}$ |
| 400 | $\alpha\frac{3^\lambda}{1^\lambda+2^\lambda+3^\lambda}$ | $\alpha\frac{2^\lambda}{1^\lambda+2^\lambda+3^\lambda}$ | $\frac{1^\lambda}{1^\lambda+2^\lambda+3^\lambda}$ | $(1-\alpha)\frac{2^\lambda}{1^\lambda+2^\lambda+3^\lambda}$ | $(1-\alpha)\frac{3^\lambda}{1^\lambda+2^\lambda+3^\lambda}$ |
| 600 | $\alpha\frac{4^\lambda}{1^\lambda+2^\lambda+3^\lambda+4^\lambda}$ | $\alpha\frac{3^\lambda}{1^\lambda+2^\lambda+3^\lambda+4^\lambda}$ | $\alpha\frac{2^\lambda}{1^\lambda+2^\lambda+3^\lambda+4^\lambda}$ | $\alpha\frac{1^\lambda}{1^\lambda+2^\lambda+3^\lambda+4^\lambda} + (1-\alpha)\frac{1^\lambda}{1^\lambda+2^\lambda}$ | $(1-\alpha)\frac{2^\lambda}{1^\lambda+2^\lambda}$ |
| 800 | $\alpha\frac{5^\lambda}{1^\lambda+2^\lambda+3^\lambda+4^\lambda+5^\lambda}$ | $\alpha\frac{4^\lambda}{1^\lambda+2^\lambda+3^\lambda+4^\lambda+5^\lambda}$ | $\alpha\frac{3^\lambda}{1^\lambda+2^\lambda+3^\lambda+4^\lambda+5^\lambda}$ | $\alpha\frac{2^\lambda}{1^\lambda+2^\lambda+3^\lambda+4^\lambda+5^\lambda}$ | $\alpha\frac{1^\lambda}{1^\lambda+2^\lambda+3^\lambda+4^\lambda+5^\lambda} + (1-\alpha)$ |

Table 8: Parameter estimates in the Markov investment choice model

| | UNQ | CRS |
|---|---|---|
| $\alpha$ | 0.614 | 0.604 |
| std. err. | 0.0239 | 0.0234 |
| $\lambda$ | -0.483 | -0.665 |
| std. err. | 0.0818 | 0.0838 |

Table 9: 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 | 0.08 | 0.61 | 0.09 | 0.10 | 0.11 | 0.13 | 0.57 |

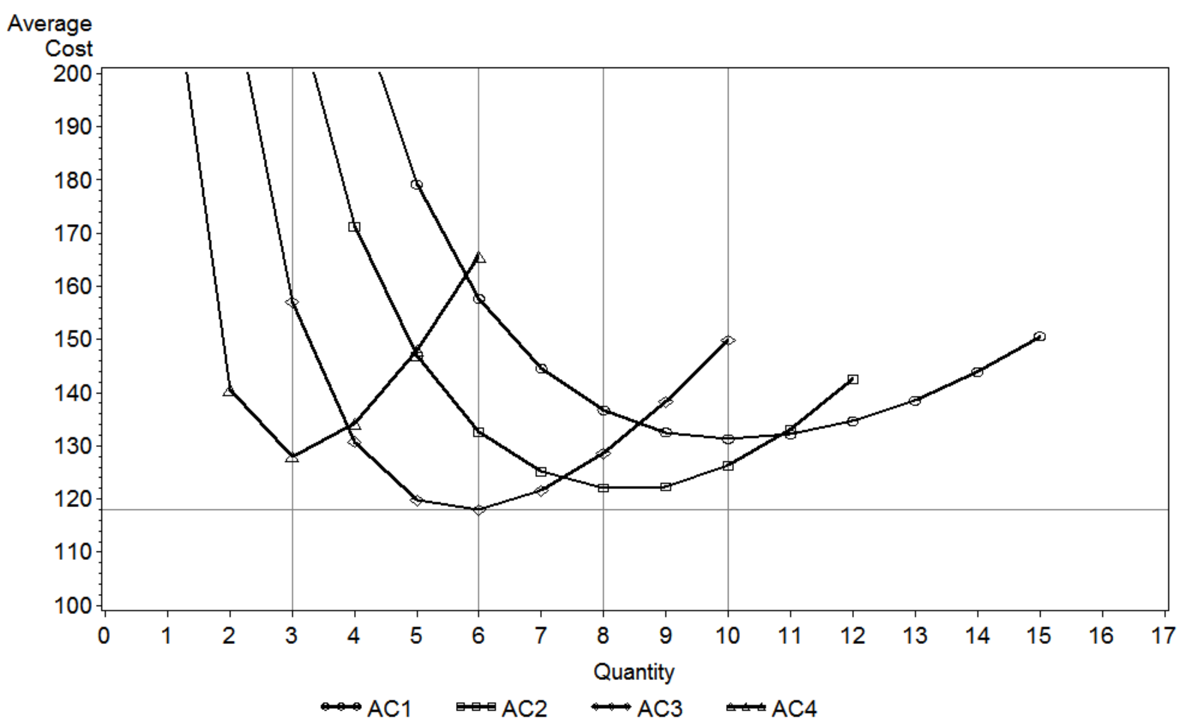


Figure 1: Average cost curves for UNQ treatment

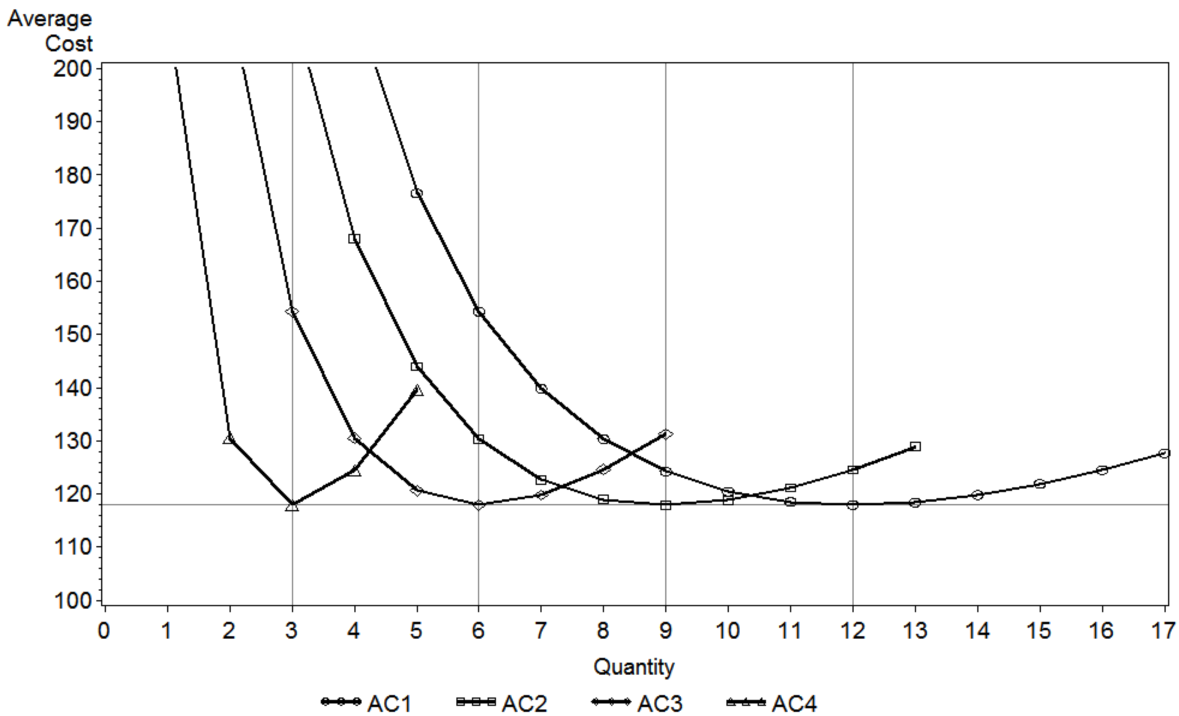


Figure 2: Average cost curves for CRS treatment

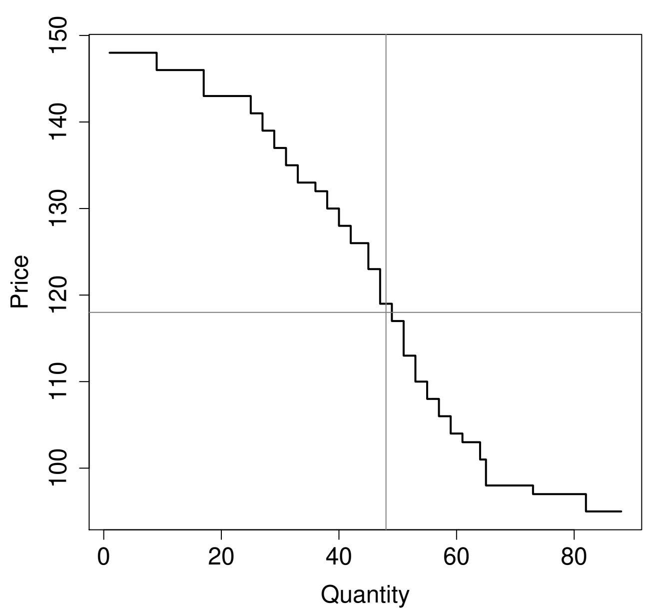


Figure 3: Market demand curve

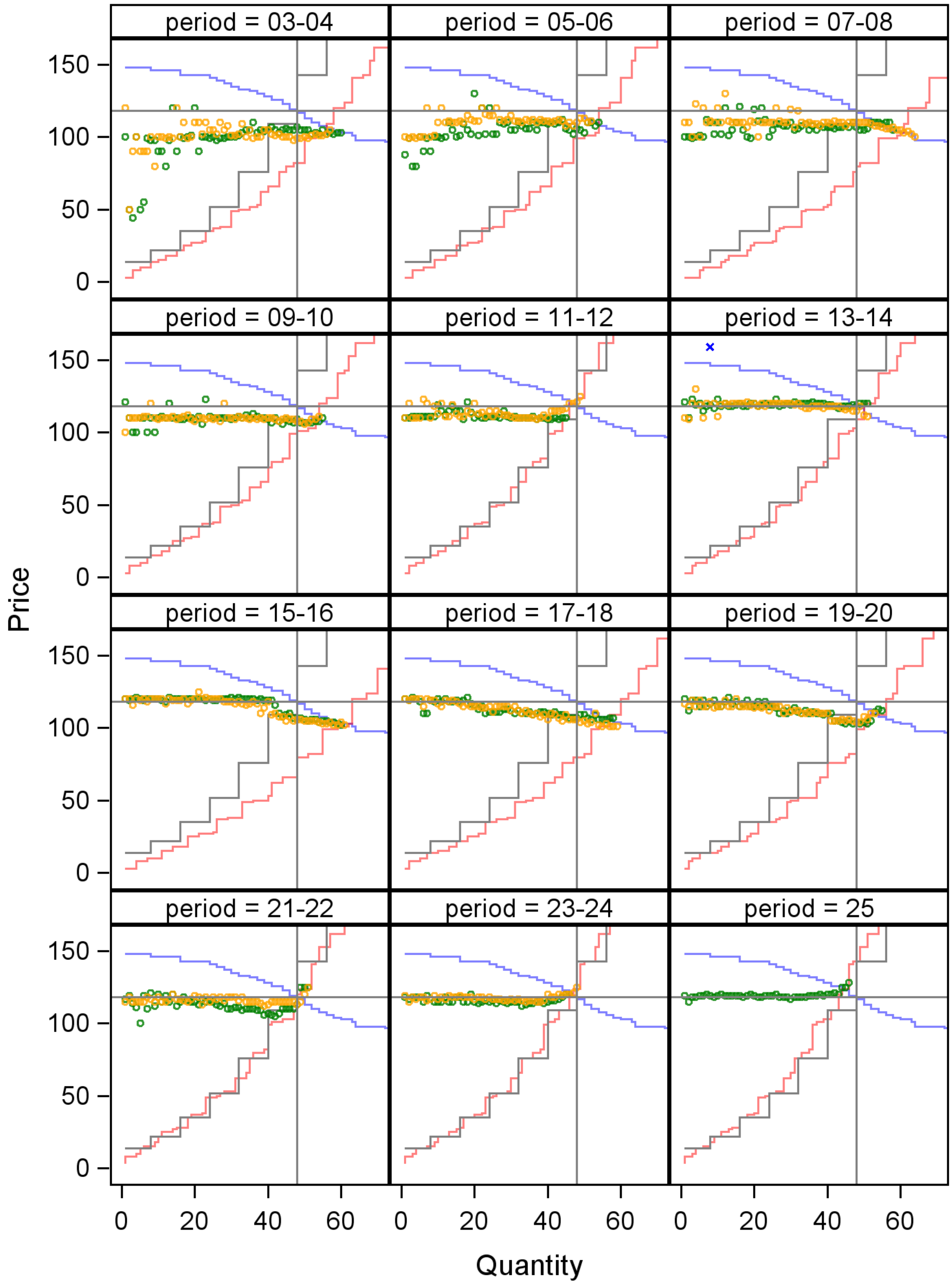


Figure 4: Demand, realized short run supply, and trades in the UNQ08 session

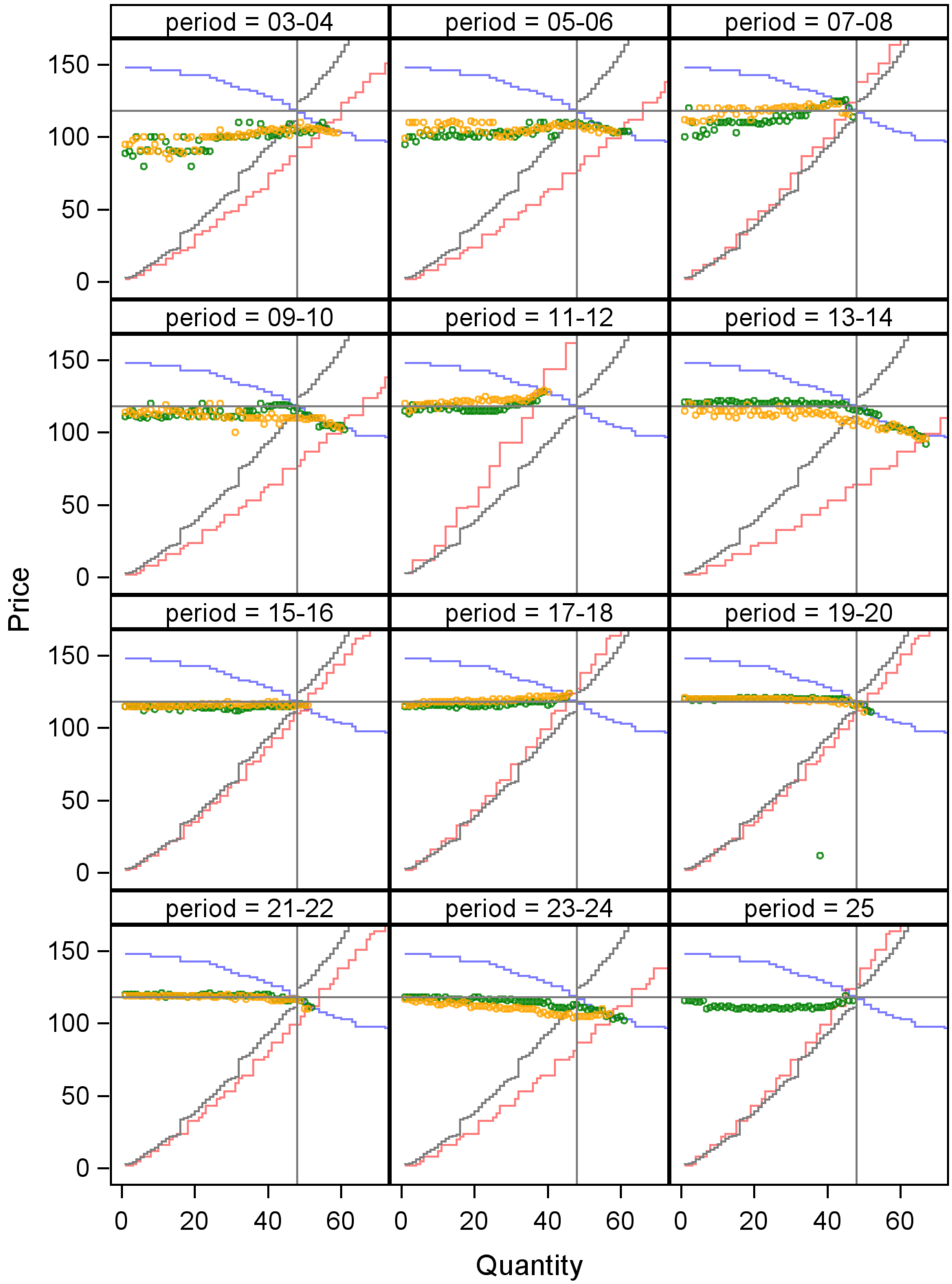


Figure 5: Demand, realized short run supply, and trades in the CRS02 session

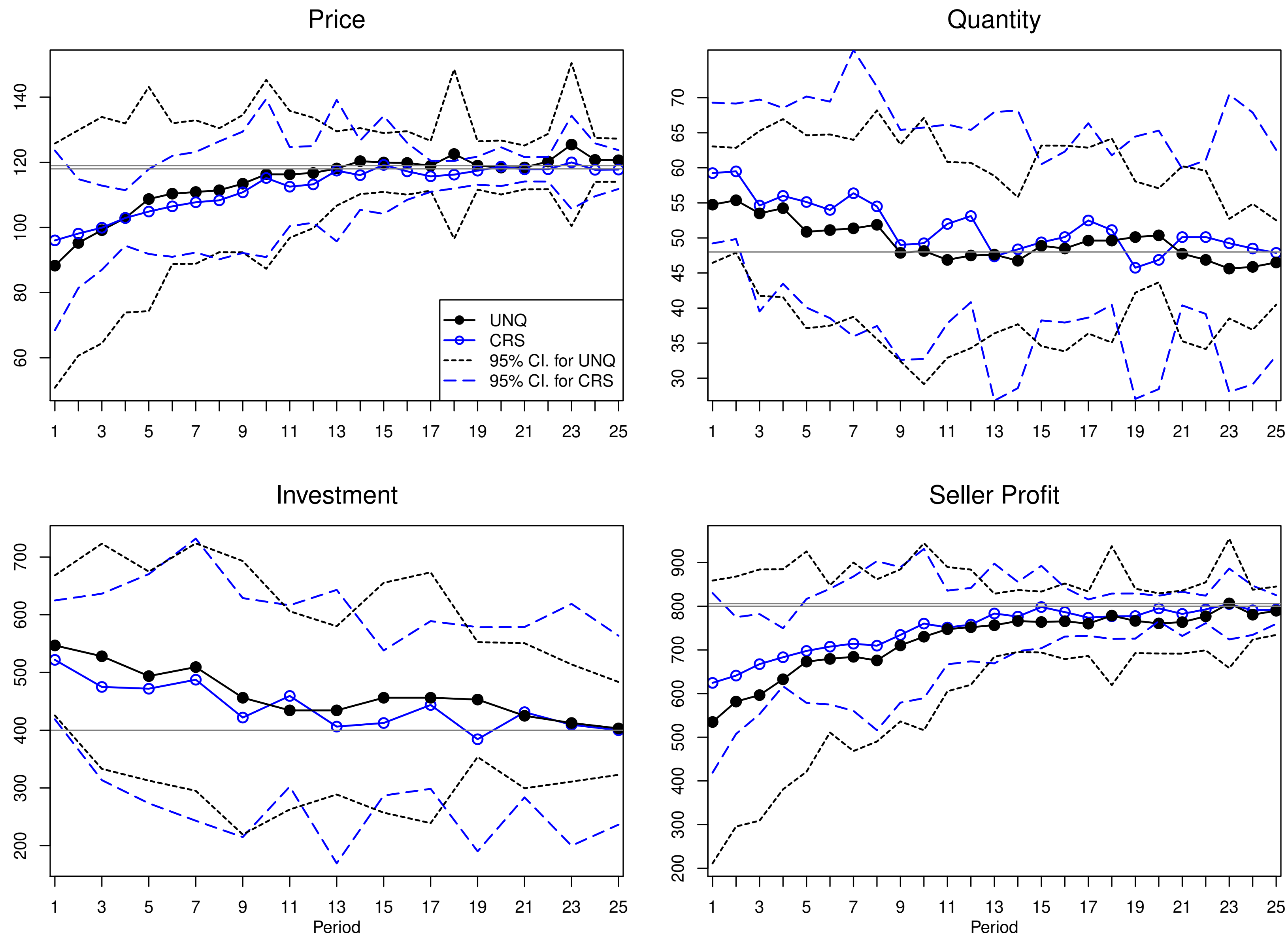


Figure 6: Time series of average price, quantity, investment, and seller profit

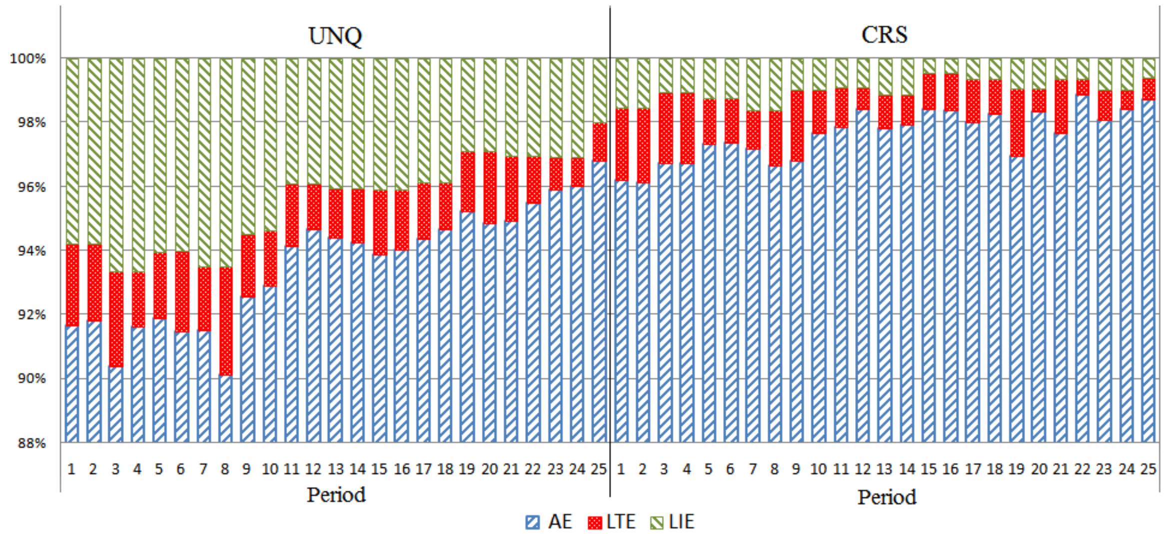


Figure 7: Allocative efficiency decomposition for each period

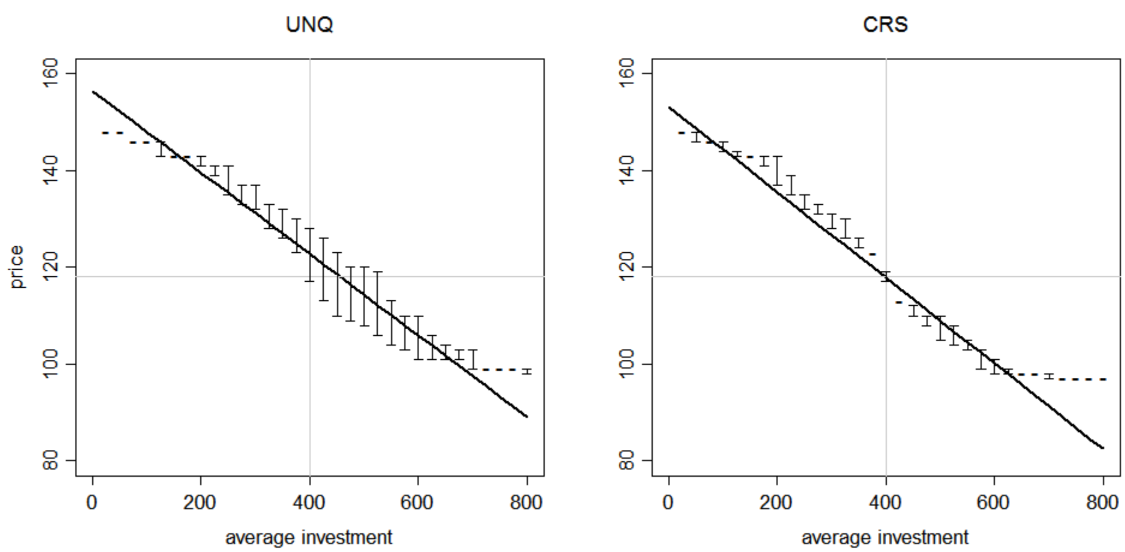


Figure 8: Estimated short run equilibrium price conditional upon Investment.
The cross bars denote the theoretical range of equilibrium prices for each possible average investment level.

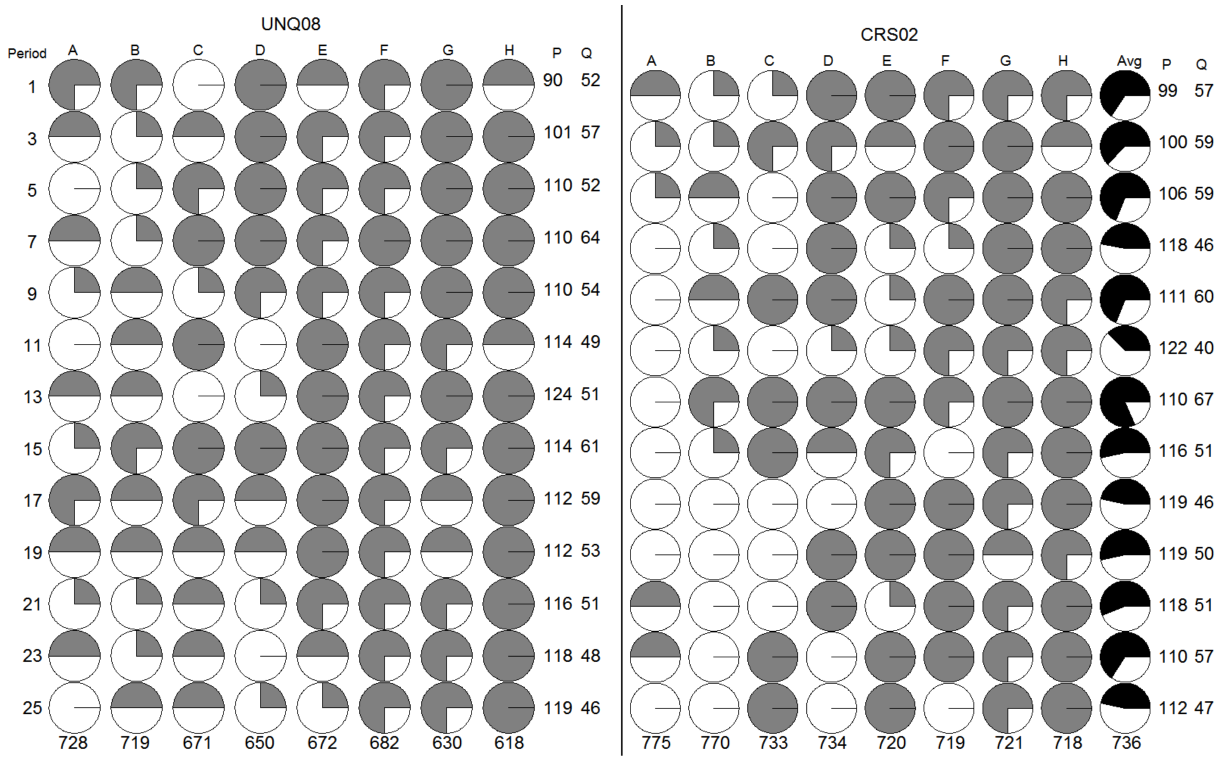


Figure 9: Individual investment choices in sessions UNQ08 and CRS02

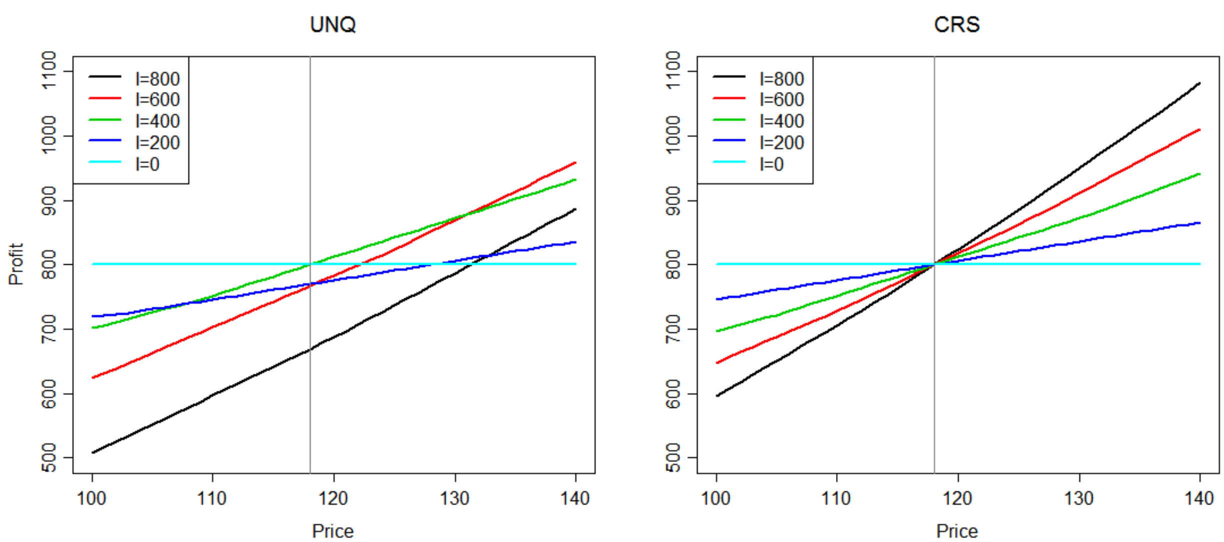


Figure 10: Profit levels for investment levels according to price

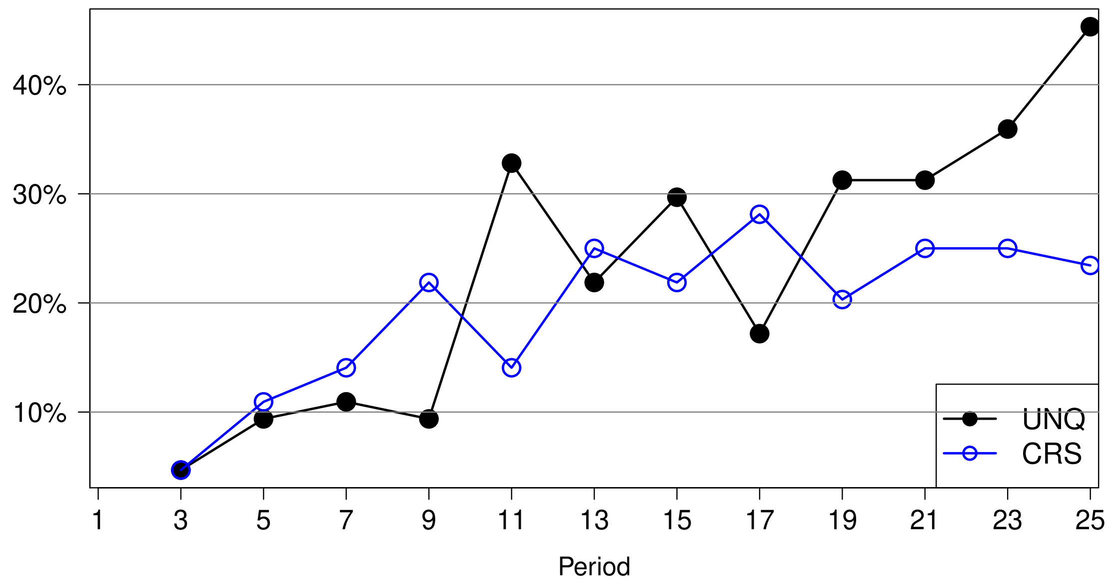


Figure 11: Proportion of best response investment decisions in each period.

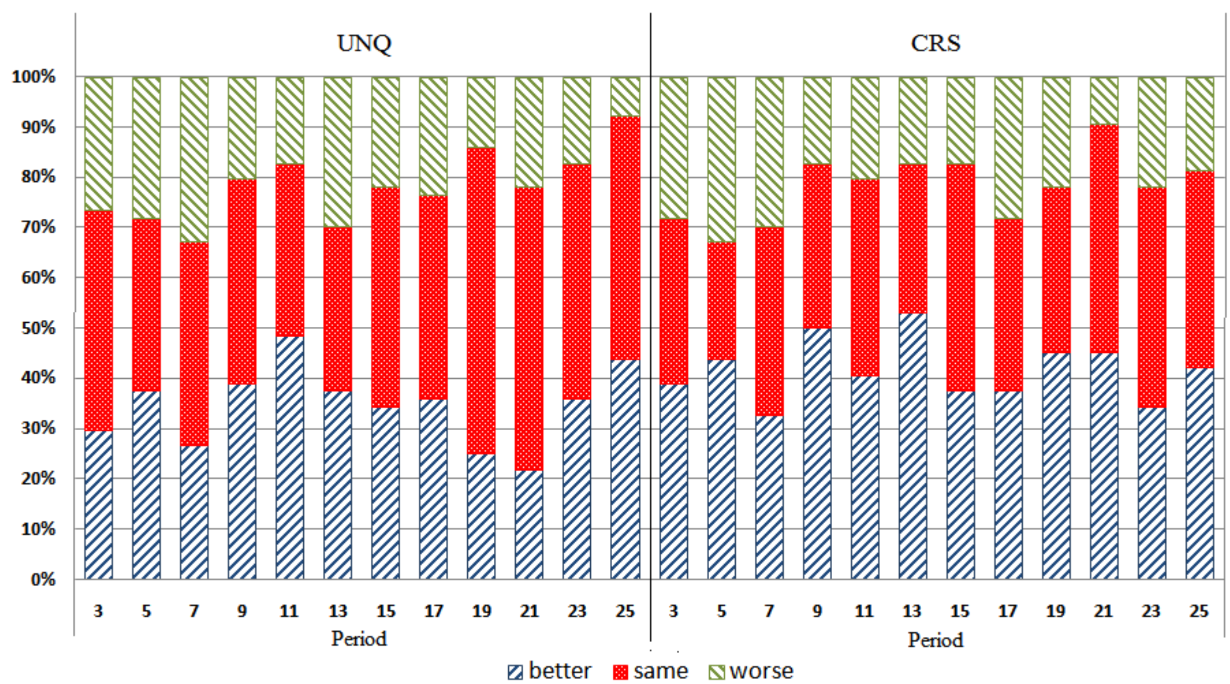


Figure 12: Proportions of better, same, and worse investment transitions

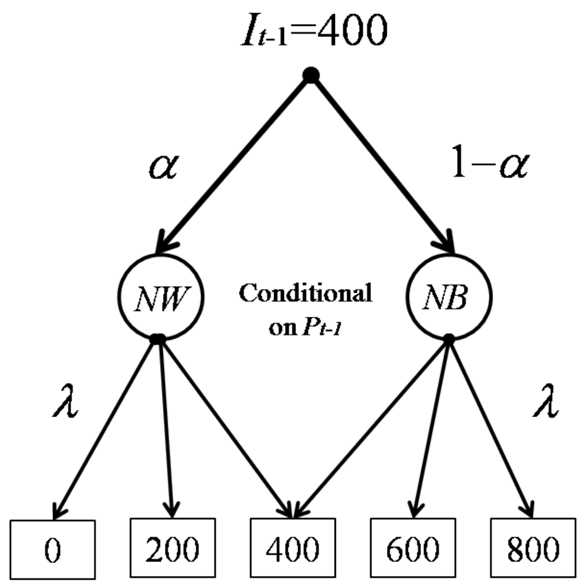


Figure 13: An example of the two stage determination of investment transition probability

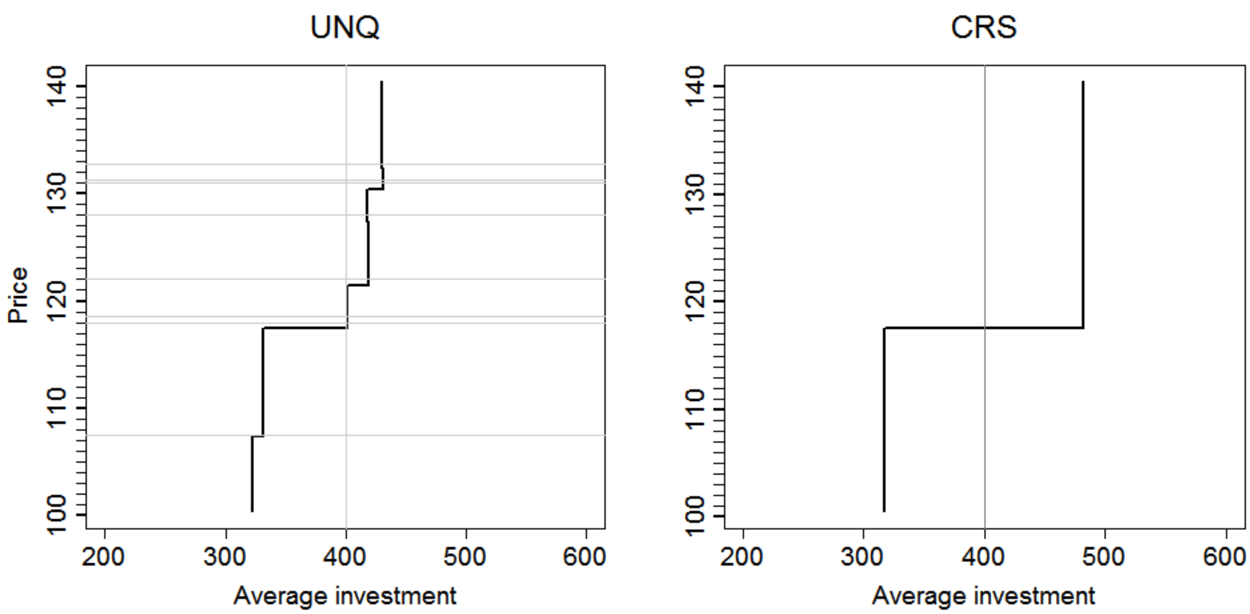


Figure 14: The average investment of limiting distributions over investment profiles

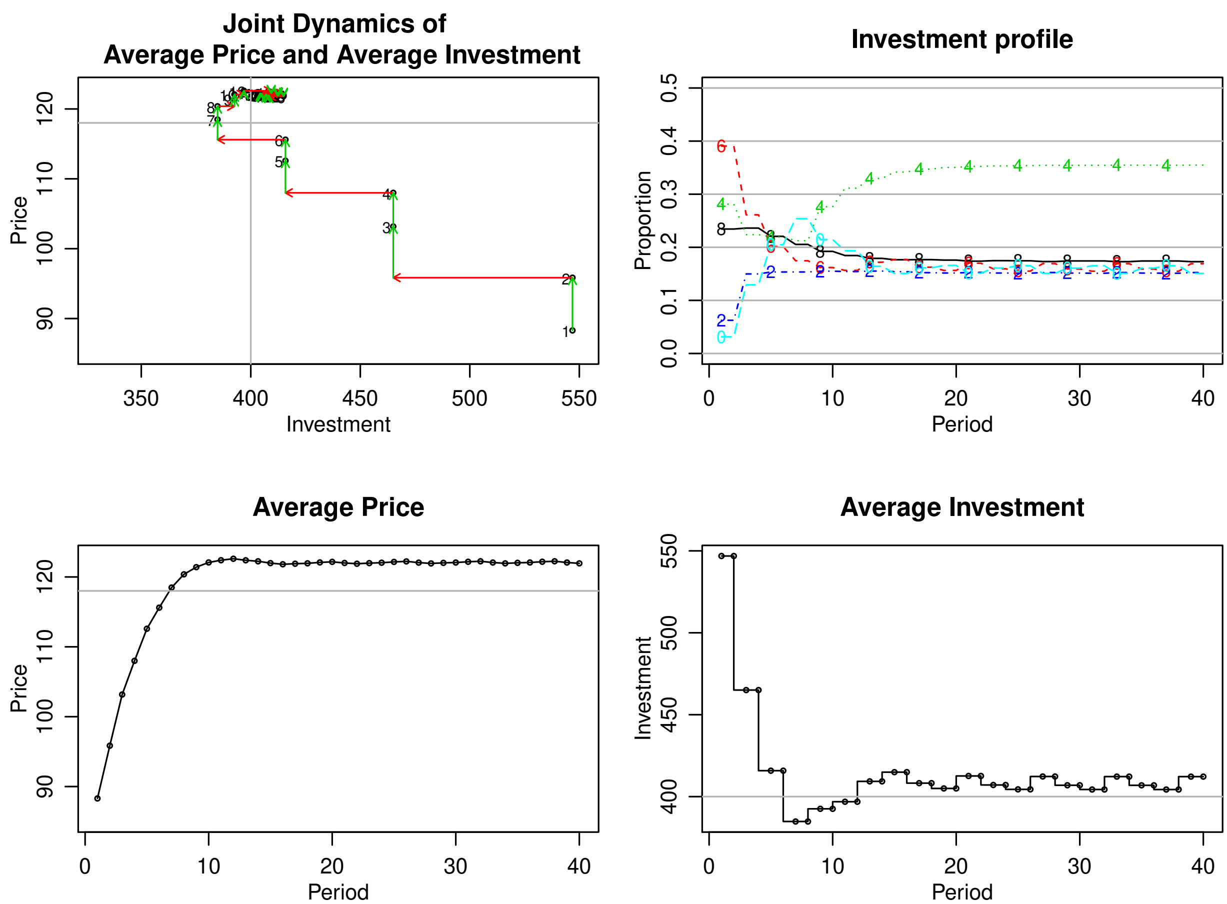


Figure 15: Expected dynamics under estimated model - UNQ treatment

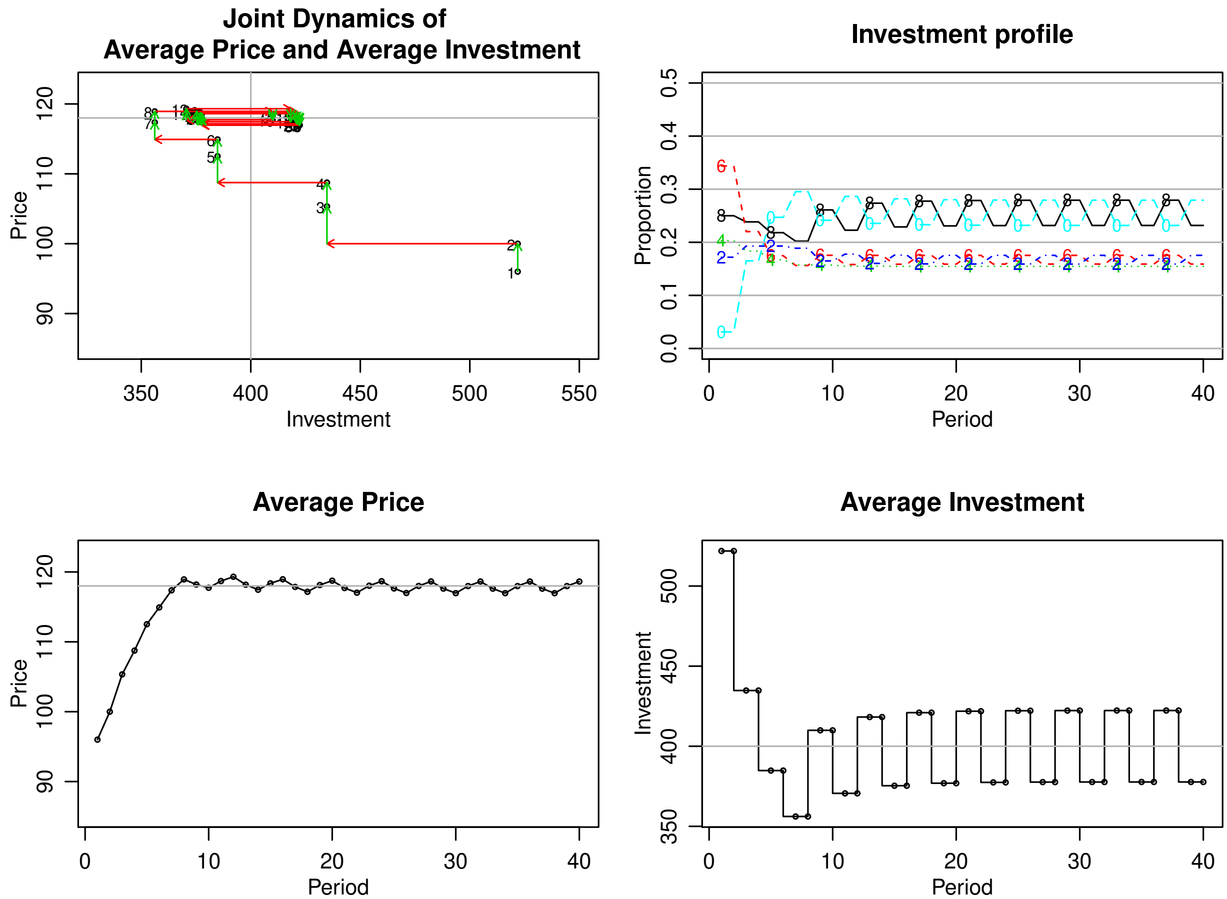


Figure 16: Expected dynamics under estimated model - CRS treatment