

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

Short title: Hayek hypothesis and long run equilibrium

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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 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. We present alternative efficient production plans as a menu of fixed and marginal cost pairs. In both environments, we observe convergence to long run competitive equilibrium prices and quantities typically within six long run decision horizons.

JEL classification: C92; D02

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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 the results and argued it provided a strong induction¹ 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 behaviour. 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. 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

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

goods or the optimal number and scale of firms in the output market.

We experimentally test the Hayek Hypothesis when the sellers' decision horizons are extended from the short run to the long run. In particular, each seller must commit to a level of a fixed input in advance of the market, and then produces-to-order in the short run. In this long run setting, the conditions of competitive equilibrium expand 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 and scale of firms participating in the market. Production technology plays a crucial role in determining the values 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. We call the former the UNQ treatment, and the latter the CRS treatment.

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 but requires all sellers to individually find the optimal production plan. In contrast, with constant returns to scale the LRE is unique only up to the aggregate production plan leaving a multiplicity of LRE in terms of the number of sellers and their sizes, as defined by the fixed input level. However this also implies that only the aggregate production plan - not individual ones - need to be optimal.

One contribution of our study is the introduction of a new procedure to induce production technologies in laboratory experiments. This procedure uses the mathematical equivalence between the cost and production function representations of a technology when there is linear pricing in inputs and outputs. In previous experimental studies examining production in markets, some we discuss shortly, subjects were presented with production function descriptions. This approach leads to the simultaneous cognitive processing of the costs and

benefits of alternative production plans. In contrast, we present subjects with a menu of cost functions from which they must choose one, allowing them to focus solely on the benefit side. The technique is promising for a variety of other experimental applications such as examining the regulation of natural monopolies, the strategic interaction between investment in cost reductions versus branding, and competitive markets with Schumpeterian innovation. Further, we believe our experimental design can be integrated into the classroom to demonstrate how the combination of competition and no barriers to entry and exit leads to cost minimization and zero economic profits.

Using this new experimental procedure, we establish surprisingly positive results regarding the Hayek Hypothesis. Our aggregate results indicate that the Hayek hypothesis extends to the long run case even when there is a multiplicity of LRE. Within the first six, out of thirteen, long run decision horizons average market prices and quantities converge to the LRE levels. Further we observe close to Pareto optimal levels of final allocations, which our design allows us to measure by allocative efficiency.

The pattern of convergence to the LRE is similar in all of our sessions. There is initial over investment that slowly falls to LRE levels. We show that prices quickly adapt to changing short run supply conditions and track the short-run partial equilibrium. Correspondingly the long run decisions on fixed input levels, which we call investment, adjust more sluggishly and noisily than output prices. It turns out that many sellers' long run investment decisions exhibit very low levels of rationality.

Sellers' investment choices coincide too little with the best responses to past or future prices to be modeled by stochastic best response 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 very well, 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, most of these studies consider production-in-advance and none consider the multiple equilibrium case like our CRS treatment. One set of these papers (Hey and Di Cagno, 1998; Riedl and van Winden, 2007, 2012) adopts the following sequence of economic activity: input goods markets, production, and finally output goods markets.² A consequence of this sequencing is that firms must bear the risk of purchasing all inputs prior to the realization of output prices. Upon 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 discernible movement towards competitive equilibrium.

A second set of double auction market papers considers general equilibrium production economies where markets for input and output goods are conducted simultaneously. Producers in these experiments 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

²Another fascinating experiment following this sequence is Crockett *et al.* (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.

economies with multiple input and output goods (Noussair *et al.*, 1995, 1997, 2007). However, in all of these cases convergence still occurs from too little production and the ratio of input to output prices from 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 production-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 these studies with partial equilibrium settings with production-in-advance are characterized by initial overproduction.

1 Experimental design

1.1 Economic environment

Our 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, each seller must set the level of one input good - the fixed input - prior to choosing the levels of production and the other input good - the variable input. A seller chooses his fixed input level in odd-numbered periods, and it remains unchanged in the subsequent even-numbered period. Third, the prices of the input goods are exogenous and constant.

The seller owns four durable units of the fixed input, which he allocates between the production of boxes and leasing at the exogenous per period price.³ Leased units of the fixed input generate a stream of revenue each period which we call ‘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 four 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* as a choice from a menu of profit bonuses and associated marginal cost schedules. This menu generates a family of short run average total cost curves, the lower envelope of which constitutes the firms’ long run average 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: 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. 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 1.⁴ Again there are four alternative short run

³Note, we prohibit a seller from increasing his stock of the fixed input by renting in this market.

⁴Let k be the input good whose level can only be adjusted in the long run time frame with price r , and l be the factor whose level can be adjusted in time with output levels with price w . Our menu of cost schedules is a discrete approximation of the Cobb-Douglas production function $q = \sqrt{kl}$ whose short run total cost function is $C(q, r, w; k) = rk + \frac{w}{k}q^2$, short run marginal cost is $MC(q, r, w; k) = \frac{2w}{k}q$, and long run average cost function is $LRAC(q, r, w) = 2\sqrt{rw}$. It’s clear from the calculation of the profit bonus the

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 precipitates indeterminacy in the market composition of firms when solving for market supply. For example, at the price of 118 the profit earned by two firms is the same when one firm produces six boxes using cost schedule #3 and the other firm exits, or when both firms produce three boxes each using cost schedule #4.

The market demand for boxes is constant for each market period and is the horizontal summation of the eight individual demands. Table 2 presents these individual demand curves as schedules of unit valuations. During the experiment, we shuffle 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 by so much that increasing either input becomes profitable. Prices in the interval $[118, 119]$ satisfy these criteria for our experiment. Second, the LRE quantity of boxes traded is 48. Third, all sellers earn zero economic profit (or slightly positive due to the discreteness of the environment), which in our experiment is the nominal profit range of $[800, 806]$ for 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 invest-

price of k equals 200, and from this we can infer the price of l is approximately 17.4. The market quantity demanded is found by substituting the equilibrium price into the market demand schedule.

ment 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.

1.2 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.

The second component is the subjects' participation in the 25 computerized double auction periods for trading boxes. Each trading period lasts 165 seconds. During the double auction buyers and sellers can respectively submit limit bids and limit 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 Renminbi, at an exchange rate of 50 to 1 and 1000 to 3, respectively. We chose the exchange rates so that, in equilibrium, a buyer's and a seller's expected earnings in Renminbi are the same.

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 System (Greiner, 2004).⁵ The experiment itself was conducted using the BASA (Buy and Sell Auction) software developed by the IBM TJ Watson Research Center.^{6,7} This software uses an interactive set of computerized instructions⁸ that the subjects read individually.⁹ 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 buyer's payment is larger than the average seller's payment because of disequilibrium outcomes in which consumer surplus exceeds, and producer surplus fails to meet, LRE levels.

⁵At 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.

⁶The double auction engine and a large part of the user interface in BASA were adopted from the GEM (General Equilibrium Market) software developed by Steven Gjerstad and Amit Shah at the IBM Thomas J. Watson Research Center. GEM was used in various studies such as Gjerstad (2007, 2013).

⁷We direct those wishing to replicate this study and for those wanting to incorporate LRE experiments into their classroom activities to a Java implementation provided by the Econport project, <http://excen.gsu.edu/longruneq/>, and developed under National Science Foundation grant number DUE-0633252 (Gjerstad and Casari, 2014).

⁸An 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.

⁹As this experiment is an investigation of market performance under decentralized private information, we did not publicly display or read any part of the instructions.

2 Evaluating the Hayek Hypothesis

We start with a data visualization of an experimental session that depicts realized short run market supply schedules, trade prices, and quantities against the respective theoretical LRE 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 denoted by the crosses. This session is typical¹⁰ 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 to the LRE prediction, and correspondingly price and quantity also converge close to their respective 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 CRS02.¹¹ 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.

¹⁰The online appendix for this paper at <http://www.jasonshachat.net/LREAppendices.pdf> contains this figure for all experimental sessions.

¹¹Due to the indeterminacy of the short run market supply, the benchmark supply curve is the average of 33 market supply schedules associated with the set of equilibrium investment profile.

2.1 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 also fall in line with the LRE. 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 5.

We take a first coarse look at the seller’s investment decisions and profits. We consider average investment levels¹² 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 also adjusts slowly 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

¹²The average is a somewhat erroneous simplified measure in the UNQ case; later we will consider the whole investment profile.

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.

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 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 sum of sellers' and buyers' market earnings and the total of the sellers' profit bonuses in the LRE. Now define MSR as the maximum possible gains given the seller's investment profile.¹³ 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, LTE , LIE , and AE , for each market period across the 8 sessions.¹⁴ These results are plotted in Figure 6. From this figure we observe that,

¹³The ratio of RG to MSR is the allocative efficiency measure often reported in experimental studies of short run markets.

¹⁴The term we drop from the approximation, $LTE \cdot LIE$, 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%.

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 want to address. Why do markets adjusts slowly from over-investment in the early periods to the LRE. What are the underlying behaviour principles and choice dynamics governing market prices and investment profiles that give rise to such slow adjustment?

3 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 jointly converge to the LRE predictions.

3.1 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). We assume prices adjust proportionally a deviation from this equilibrium, allowing for different adjustment rates for odd- and even-numbered periods. This leads us to estimate the following distributed lag model:

$$\bar{P}_{s,t} - \bar{P}_{s,t-1} = \alpha_s + \beta * (\bar{P}_{s,t-1} - P^e(\mathbf{I}_{s,t})) + \gamma * \mathbb{1}_{(t \text{ is even})} * (\bar{P}_{s,t-1} - P^e(\mathbf{I}_{s,t})) + u_{s,t}$$

in which $\bar{P}_{s,t}$ is the average trading price in period t of session s , $\mathbf{I}_{s,t}$ is the 8-element investment profile in period t of session s , $\mathbb{1}_{\langle \cdot \rangle}$ is the indicator function, and P^e is a function that returns the equilibrium price when the short run market supply is determined by $\mathbf{I}_{s,t}$. 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 suggest 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 $\beta \neq -1$. In both treatments the estimated β is about -0.30. Further notice that γ is not significant for either treatment. This suggests if investment profiles are constant across periods, we can expect geometric convergence, at the same rate in odd- and even-numbered periods, to equilibrium prices.

A constant convergence rate across periods reflects a lack of increased pricing efficiency we would expect in even-numbered periods due to fixed investment profiles and the benefit of the previous odd-numbered period price discovery. In the appendix we explore this issue by examining the transaction-by-transaction price adjustment. We briefly summarize those results. First, prices within a period tend not to adjust until the period expiration approaches and there is either a shortage (empty ask queue) or surplus (empty bid queue). At this point prices will adjust toward (and usually to) the short run equilibrium price for the current investment profile. Thus closing transaction prices are those aggregating information about the short run market conditions. The key failure is that this information does not fully carry over to the opening prices in the subsequent even-numbered periods.

3.2 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 one with the lowest average investment to the one with 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 a 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 period¹⁵, 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. Albeit, 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 the extent to which individual investment decisions are suboptimal for much of the experiment.

3.2.1 How rational are investment choices?

We assess the optimality of investment choices by first considering 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 expected price p and investment level I . When considering the value of alternative I 's, we assume a seller uses this profit function and sets this price

¹⁵For period 25, the last trading period, the average price and quantity are for that period itself.

expectation equal to the average price from the previous period $\bar{p}_{t-1}$. However, our results are robust to this choice. In unreported analysis, we find essentially no differences when we set this price expectation as the average of the previous two period prices, the previous closing price, or when we assume sellers are forward looking with rational expectations and set p equal to the average price of the subsequent one or two periods.

Let's consider how often a seller i 's investment choice in period t , 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 ask whether the sellers is more likely to transit to an investment level offering higher expected profit than to one offering lower expected profit. Specifically does the following inequality hold,

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

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. 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.

3.2.2 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 behavioural 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 shown investment decisions are inconsistent with the higher value implies higher choice probability premise. 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.

In our 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 offering 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 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,

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

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

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 level 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 level 0 and 800 is 5. We use the following weighting function to determine an investment level's assigned share of probability measure,

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

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;

$$\begin{aligned}\Pr(I_{it} = j | I_{it-1}) &= \alpha * \mathbb{1}_{\langle j \in NW(\bar{p}_{t-1}, I_{it-1}) \rangle} * w(j | I_{it-1}, NW(\bar{p}_{t-1}, I_{it-1}), \lambda) \\ &\quad + (1 - \alpha) * \mathbb{1}_{\langle j \in NB(\bar{p}_{t-1}, I_{it-1}) \rangle} * w(j | I_{it-1}, NB(\bar{p}_{t-1}, I_{it-1}), \lambda).\end{aligned}$$

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 $\bar{p}_{t-1}$ 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 fourth 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 UNQ treatment. However, in both cases the parameter estimate is significant and we reject that there is no bias, i.e. $\lambda = 0$.

Let's see how the estimated model translates into transition probabilities between investment levels. Since sessions in our experiment typically start off with prices 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 continues to do so - which is the profit maximizing choice at the price of 115 - and is almost 75% for both treatments.

3.3 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 may be 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 12. The results here are the same, except there is an even more well defined convergence to a cobweb 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 an interesting cycle between the investment level 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. As previously noted, some subjects do exhibit this pattern of switching between the extreme investment levels as price oscillates around the equilibrium level of 118. This suggests there is individual heterogeneity in the rationality of investment decisions. Remarkably our Markov investment model, which assumes homogeneity, generates this pattern at the aggregate level.

Overall, combining the adaptive price formation model with the boundedly rational Investment model does a notable job of mimicking the dynamics of the experimental data as it converges to the LRE. Furthermore, it provides a demonstration of how a behavioural rule, incorporating minimal rationality, used in conjunction with the double auction trading institution robustly generates LRE outcomes.

4 Discussion

Can a decentralized allocation process implement competitive equilibrium allocations in an economy with long and short run production decision horizons? While providing a positive answer to this question, we extend Smith's (1962, 1982) seminal 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 either a U-shaped or constant long run average cost curve, replication of the market leads to the competitive LRE in typically less than six long run decision horizons.

This convergence was surprising given that the vast majority of long run investment decisions exhibit less rationality than stochastic best response.

A second surprising aspect is that convergence almost uniformly occurs from initial over investment and corresponding overproduction and underpricing in the output good market. This is surprising because almost all other experimental studies on production economies observe initial under investment in production factors and corresponding underproduction and overpricing in the output good market. We conjecture this arises from the different economic impacts of production-to-order versus production-in-advance, where the former leads to elastic short run supply functions and the latter to perfectly inelastic short run supply curves. However, this over investment could also come from some behavioural artefacts of our experimental design. First, there could be a strong activity bias that leads subjects to enter the market and choose schedules allowing them to make more trades. While our assessment of investment rationality has been quite pessimistic, it is actually fair to note that many subjects - enough to get to the LRE - subjects are willing to exit the market at low prices and endure the two periods of no stimuli. Second, we endow our subjects with the long run input while other studies require subjects to borrow money from the experimenter to purchase input goods. This allows us to put the range of payoffs as gains, while other studies clearly have losses in the range of payoffs. Thus, it's reasonable to expect loss aversion to impact subjects' decisions in these production-in-advance settings. Discrimination of the effects would require a different experimental design.

Despite these caveats, we believe our innovative experimental design can be leveraged to answer important open questions. For example, what are the differential responses and dynamics when the prices of fixed inputs change versus when the prices of variable inputs change? Also, what are the different impacts of taxing output goods, fixed inputs, and variable inputs? What role does the length between investment decisions, and the lag of implementation, play when technology allows for natural monopolies?

A Intra-period price dynamics

We examine the transaction level data to investigate how information about short run supply is aggregated by price. Recall, that Figures 4 and 3 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 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.¹⁶ Consequently, while the price adjustments to late period surpluses and shortages are information flows that should facilitate the Hayek hypothesis, but 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 trans-

¹⁶This inter-period price pattern is an empirical regularity of double auction market experiments (Plott, 2008).

action price,

$$\begin{aligned}\Delta P_{stj} = \alpha &+ \beta_1 * \mathbb{1}_{\langle \text{shortage} \rangle}(h_{stj}, P_{st,j-1}) * (\underline{C}(h_{stj}) - P_{st,j-1}) \\ &+ \beta_2 * \mathbb{1}_{\langle \text{surplus} \rangle}(h_{stj}, P_{st,j-1}) * (P_{st,j-1} - \overline{V}(h_{stj})) \\ &+ (\beta_3 + \beta_4 * \mathbb{1}_{\langle t \text{ is odd} \rangle}) * (P_{s,t-1}^C - P_{st,j-1}) + \varepsilon_{stj}\end{aligned}$$

The dependent value, ΔP_{stj} , 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_{stj} , 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 $\underline{C}(h_{stj})$ 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 $\overline{V}(h_{stj})$ selects the maximum of the remaining unit valuations for the market state, and is zero if there is no remaining demand. The dummy variables $\mathbb{1}_{\langle \text{shortage} \rangle}(h_{stj}, P_{st,j-1})$ and $\mathbb{1}_{\langle \text{surplus} \rangle}(h_{stj}, P_{st,j-1})$ are indicator functions for whether the market is currently in shortage and surplus respectively. Finally, the closing price of the previous period is denoted P_{st-1}^C .

Let's consider the coefficients in this model. When the market is in a shortage, price should rise enough that the lowest cost remaining unit can be sold profitably. This suggests β_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 β_2 should be less than negative one. Parameter β_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 β_4 should be the negative of β_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 9 we report the estimated random effects specification estimation for each treatment. For both treatments we find significantly positive estimates of β_1 implying that price will increase when there is a shortage. In the CRS treatment β_1 is greater than one making it large enough to render the first extra-marginal unit of supply profitable. However, in the UNQ treatment β_1 is less than one suggesting when there is a shortage the seller holding the first extra-marginal 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 loss for a reason why. When the market is in a surplus state, and estimated values of β_2 are less than negative one for both treatments implying that price will decrease enough to make the first extra-marginal unit of demand to inter-marginal.

The estimates of β_3 and β_4 reveal aspects of how market price absorbs information about the state of short run supply. First, β_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, β_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 participants 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 only partially is carried across market periods.

References

- Bosch-Domènech, A. and Silvestre, J. (1997). ‘Credit constraints in general equilibrium: experimental results’, *The Economic Journal*, vol. 107(444), pp. 1445–1464.
- Camerer, C. and Ho, T.H. (1999). ‘Experience-weighted attraction learning in normal form games’, *Econometrica*, vol. 67(4), pp. 827–874.
- Crockett, S., Smith, V.L. and Wilson, B.J. (2009). ‘Exchange and specialisation as a discovery process’, *The Economic Journal*, vol. 119(539), pp. 1162–1188.
- Gjerstad, S. (2007). ‘The competitive market paradox’, *Journal of Economic Dynamics and Control*, vol. 31(5), pp. 1753–1780.
- Gjerstad, S. (2013). ‘Price dynamics in an exchange economy’, *Economic Theory*, vol. 52(2), pp. 461–500.
- Gjerstad, S. and Casari, M. (2014). ‘Long-run equilibrium capital adjustment software’, <http://excen.gsu.edu/longruneq/>, last accessed: 21 October 2014.
- Goodfellow, J. and Plott, C.R. (1990). ‘An experimental examination of the simultaneous determination of input prices and output prices’, *Southern Economic Journal*, vol. 56(4), pp. 969–983.
- Greiner, B. (2004). ‘An online recruitment system for economic experiments’, in (K. Kremer and V. Macho, eds.), *Forschung und wissenschaftliches Rechnen*, pp. 79–93, vol. 63 of *Ges. für Wiss. Datenverarbeitung*, GWDG Bericht.
- Hey, J.D. and Di Cagno, D. (1998). ‘Sequential markets: An experimental investigation of clower’s dual-decision hypothesis’, *Experimental Economics*, vol. 1(1), pp. 63–85.
- Mckelvey, R.D. and Palfrey, T.R. (1995). ‘Quantal response equilibria for normal form games’, *Games and Economic Behavior*, vol. 10(1), pp. 6–38.
- Mestelman, S. and Welland, D. (1987). ‘Advance production in oral double auction markets’, *Economics Letters*, vol. 23(1), pp. 43–48.
- Mestelman, S. and Welland, D. (1988). ‘Advance production in experimental markets’, *Review of Economic Studies*, vol. 55(4), pp. 641–654.
- Noussair, C.N., Plott, C.R. and Riezman, R.G. (1995). ‘An experimental investigation of the patterns of international trade’, *American Economic Review*, vol. 85(3), pp. 462–91.
- Noussair, C.N., Plott, C.R. and Riezman, R.G. (1997). ‘The principles of exchange rate determination in an international financial experiment’, *Journal of Political Economy*, vol. 105(4), pp. 822–61.
- Noussair, C.N., Plott, C.R. and Riezman, R.G. (2007). ‘Production, trade, prices, exchange rates and equilibration in large experimental economies’, *European Economic Review*, vol. 51(1), pp. 49–76.
- Plott, C.R. (2008). ‘Properties of disequilibrium adjustment in double auction markets’, in (C. R. Plott and V. L. Smith, eds.), *Handbook of experimental economics results*, pp. 16–21, vol. 1, chap. 1, Amsterdam: Elsevier.
- Riedl, A. and van Winden, F.A. (2007). ‘An experimental investigation of wage taxation and

- unemployment in closed and open economies', *European Economic Review*, vol. 51(4), pp. 871–900.
- Riedl, A. and van Winden, F.A. (2012). 'Input versus output taxation in an experimental international economy', *European Economic Review*, vol. 56(2), pp. 216–232.
- Selten, R. and Stoecker, R. (1986). 'End behavior in sequences of finite prisoner's dilemma supergames a learning theory approach', *Journal of Economic Behavior & Organization*, vol. 7(1), pp. 47 – 70.
- Smith, V.L. (1962). 'An experimental study of competitive market behavior', *Journal of Political Economy*, vol. 70(2), pp. 111–137.
- Smith, V.L. (1976). 'Experimental economics: Induced value theory', *American Economic Review*, vol. 66(2), pp. 274–279.
- Smith, V.L. (1982). 'Markets as economizers of information: Experimental examination of the "hayek hypothesis"', *Economic Inquiry*, vol. 20(2), pp. 165–179.
- Von Hayek, F.A. (1945). 'The use of knowledge in society', *American Economic Review*, vol. 35(4), pp. 519–530.

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

[illegible]

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 Renminbi

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: Regression results: Inter-period price dynamics

Variable	UNQ		CRS	
	Coefficient	<i>t</i> -stat	Coefficient	<i>t</i> -stat
Dummy session 1	1.07	1.01	−1.18	−1.33
Dummy session 2	1.29	1.21	0.69	0.79
Dummy session 3	1.93	1.81	0.37	0.43
Dummy session 4	−1.49	−1.35	0.62	0.70
Dummy session 5	0.42	0.39	−0.89	−1.01
Dummy session 6	0.55	0.52	0.51	0.58
Dummy session 7	−0.89	−0.79	−0.04	−0.05
Dummy session 8	0.86	0.81	0.28	0.32
$\bar{P}_{s,t-1} - P^e(\mathbf{I}_{s,t})$	−0.31	−6.85	−0.30	−8.15
$\mathbb{1}_{\langle t \text{ is even} \rangle} * (\bar{P}_{s,t-1} - P^e(\mathbf{I}_{s,t}))$	−0.026	−0.44	−0.06	−0.99
Adjusted R^2	0.34		0.40	
F -test that	F -stat	p -value	F -stat	p -value
$\alpha_1 = \dots = \alpha_8 = 0$	1.14	0.34	0.57	0.80
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 for the Markov investment choice model

	UNQ	CRS
α	0.596	0.602
std. err.	0.0235	0.0226
λ	-0.666	-0.366
std. err.	0.0839	0.0849

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
I_{t-1}	0	0.74	0.09	0.07	0.06	0.05	0.71	0.09	0.07	0.07	0.06
	200	0.17	0.48	0.17	0.10	0.09	0.26	0.47	0.10	0.09	0.08
	400	0.19	0.09	0.55	0.09	0.07	0.16	0.19	0.41	0.13	0.11
	600	0.09	0.11	0.15	0.49	0.16	0.12	0.13	0.15	0.42	0.17
	800	0.07	0.08	0.10	0.13	0.61	0.09	0.10	0.11	0.13	0.56

Table 9: Regression results: Intra-period price dynamics

Variable	UNQ		CRS	
	Coefficient	t -stat	Coefficient	t -stat
Mean of α_{st}	0.22	1.68	0.13	0.95
$\mathbb{1}_{\langle \text{shortage} \rangle}(h_{stj}, P_{st,j-1}) * (\underline{C}(h_{stj}) - P_{stj-1})$	0.34	2.18	1.06	7.30
$\mathbb{1}_{\langle \text{suplus} \rangle}(h_{stj}, P_{st,j-1}) * (P_{stj-1} - \bar{V}(h_{stj}))$	-1.29	-5.67	-1.43	-3.30
$(P_{s,t-1}^C - P_{st,j-1})$	0.19	9.24	0.19	8.51
$\mathbb{1}_{\langle t \text{ is odd} \rangle} * (P_{s,t-1}^C - P_{st,j-1})$	-0.00	-0.15	-0.02	-0.66
Variance of α_{st}	2.45		2.81	
Variance of ϵ_{st}	12.64		11.07	
R -square	0.10		0.10	

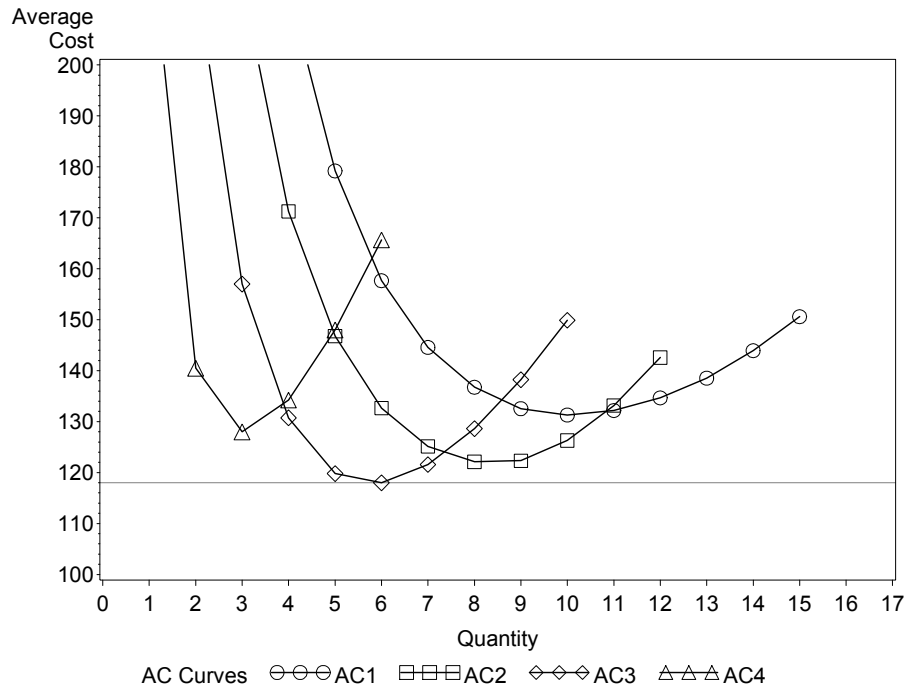


Figure 1: Average cost curves for UNQ treatment

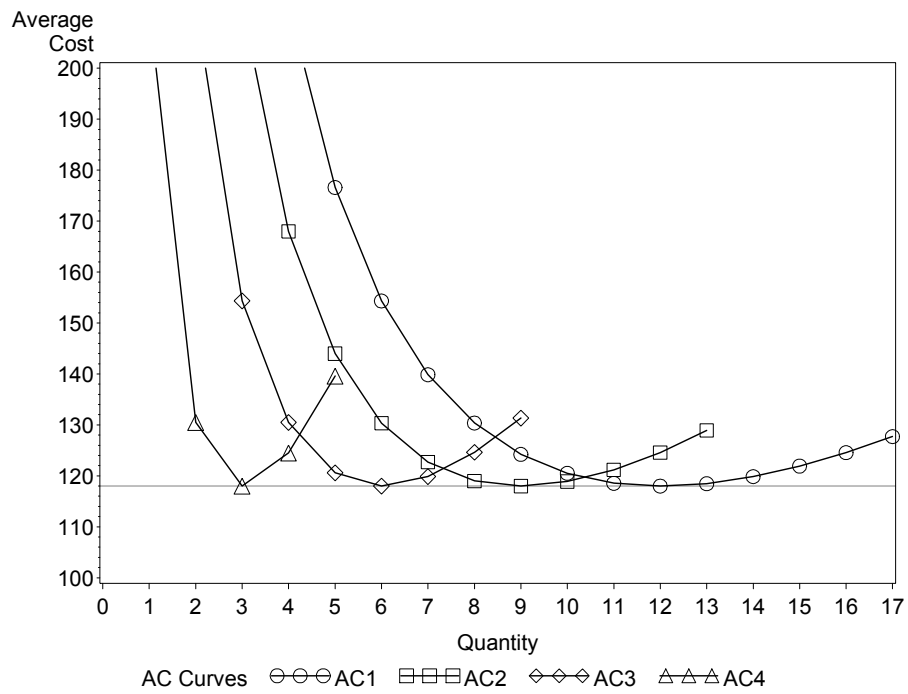


Figure 2: Average cost curves for CRS treatment

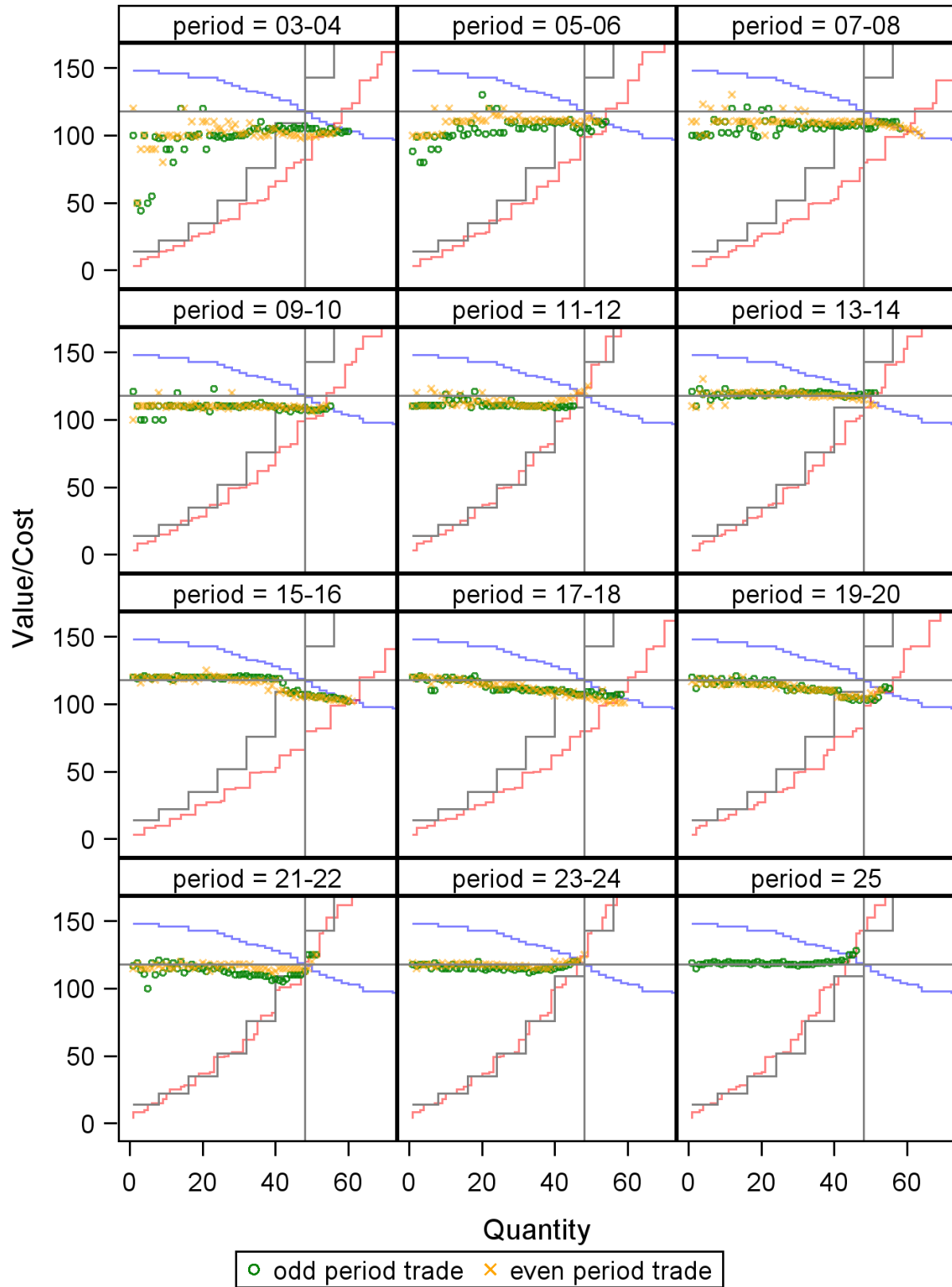


Figure 3: Demand, realized short run supply, and trades in the UNQ08 session

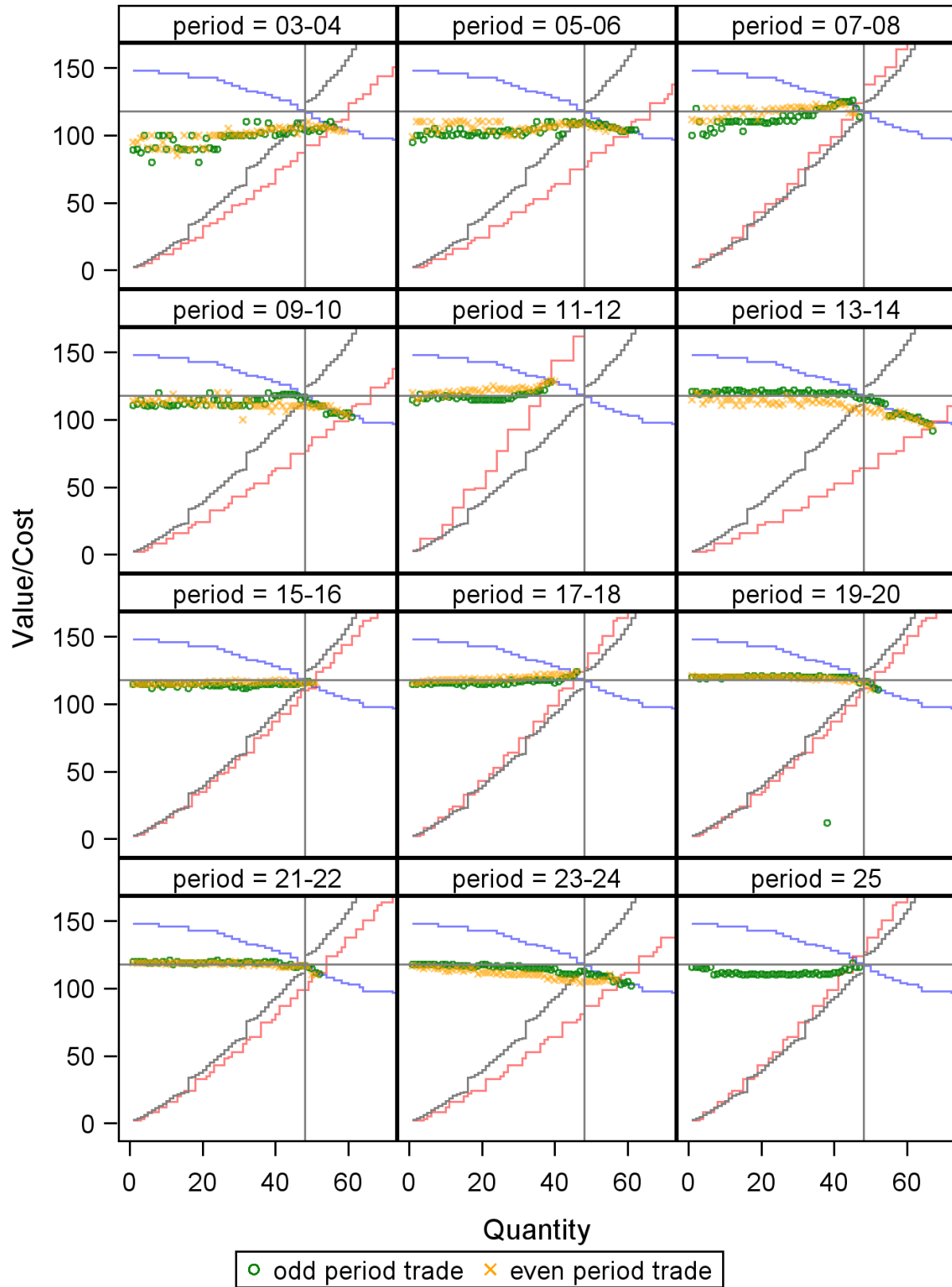


Figure 4: Demand, realized short run supply, and trades in the CRS02 session

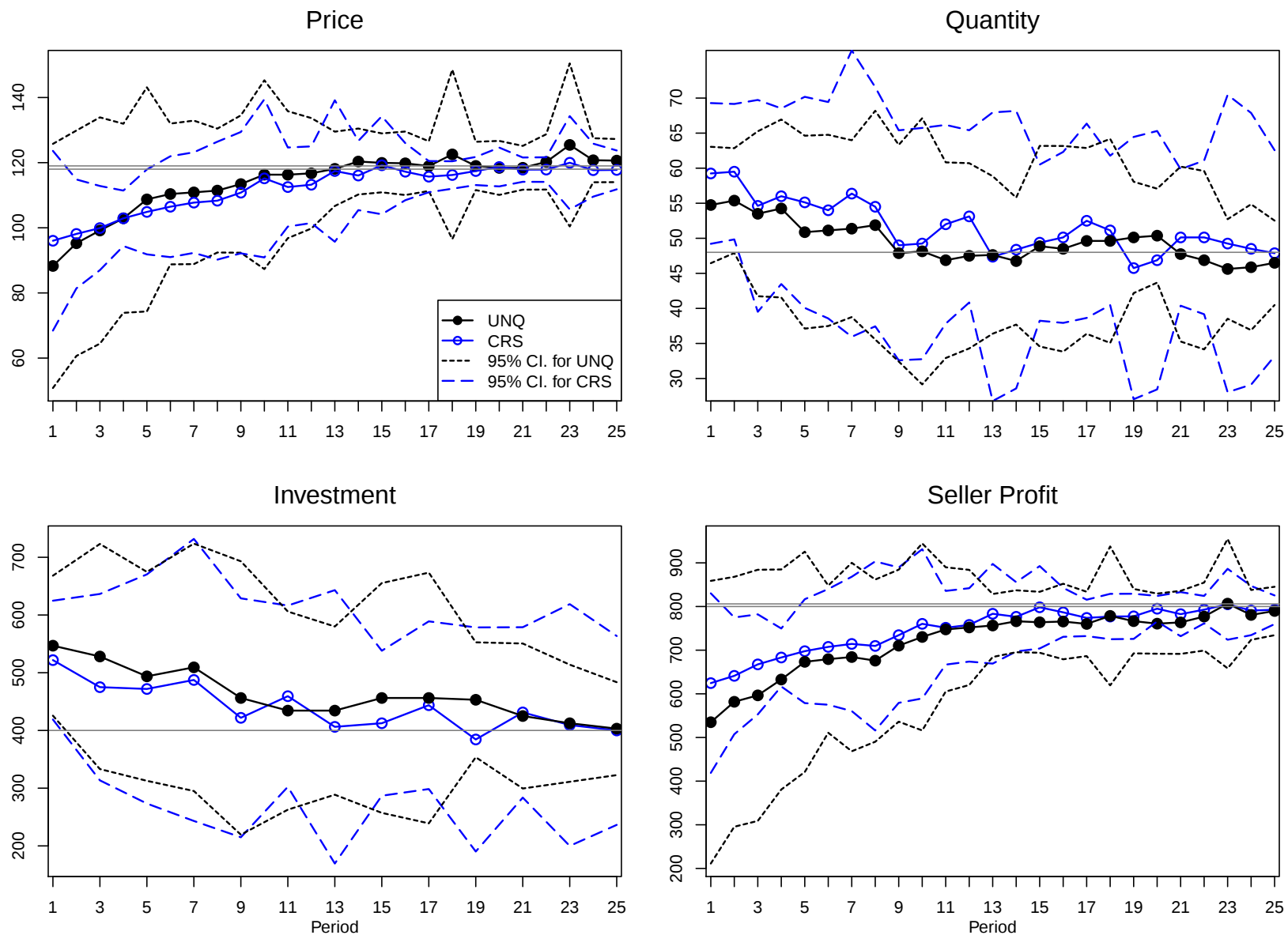


Figure 5: Time series of average price, quantity, investment, and seller profit

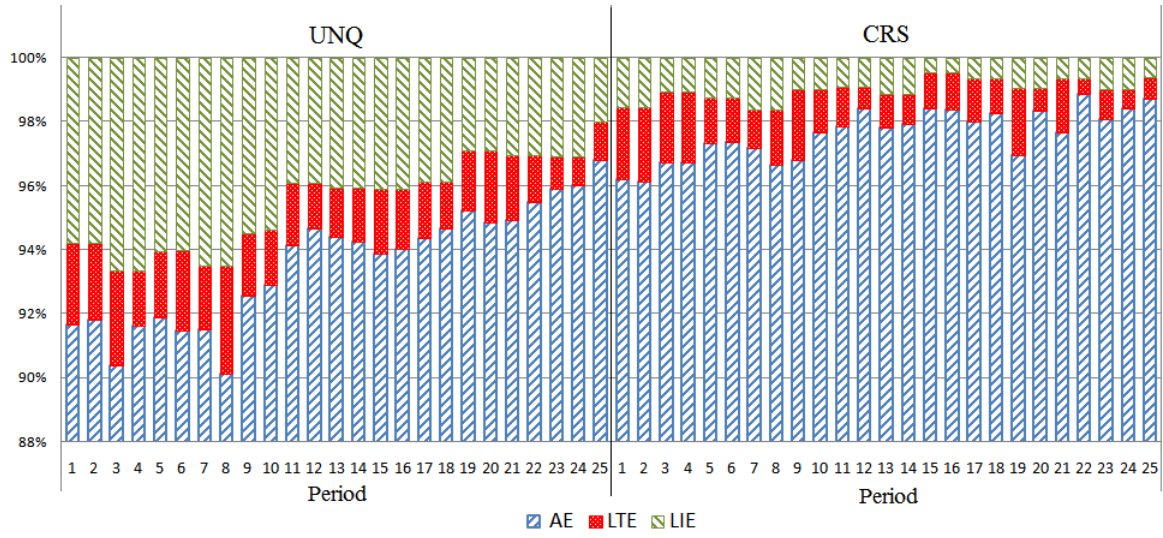


Figure 6: Allocative efficiency decomposition for each period

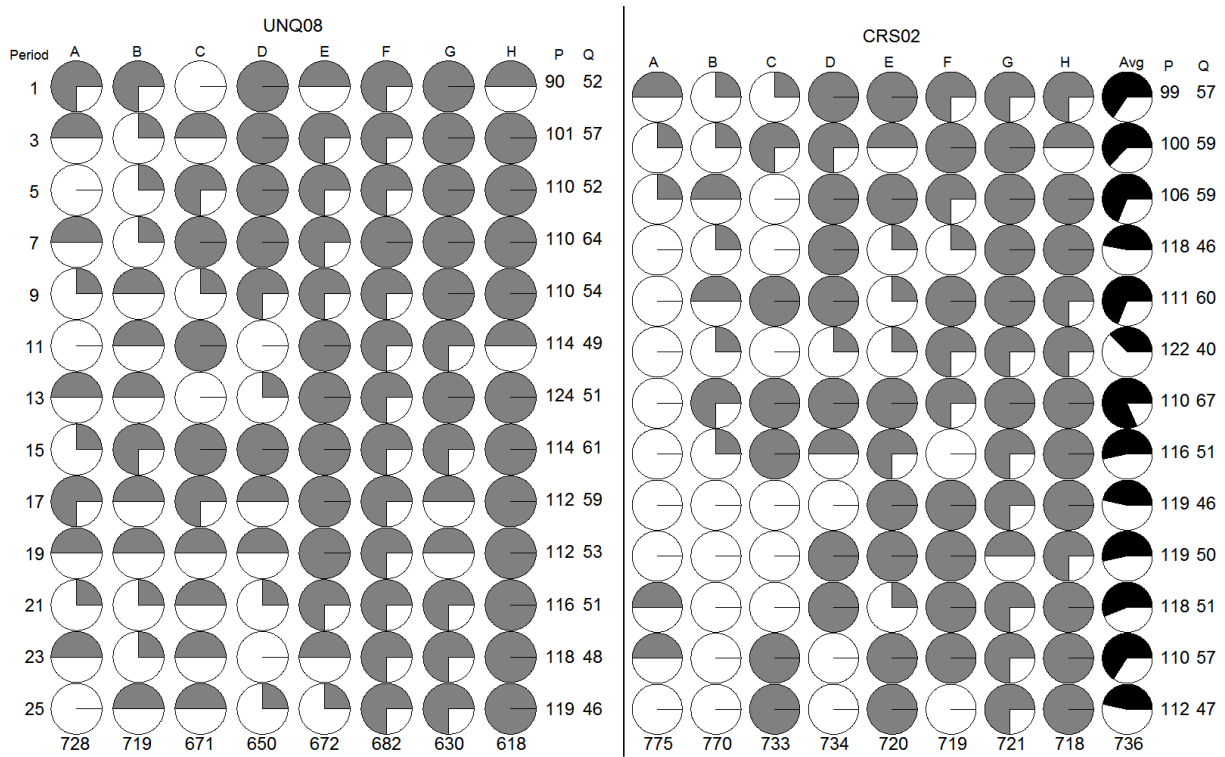


Figure 7: Individual investment choices in sessions UNQ08 and CRS02

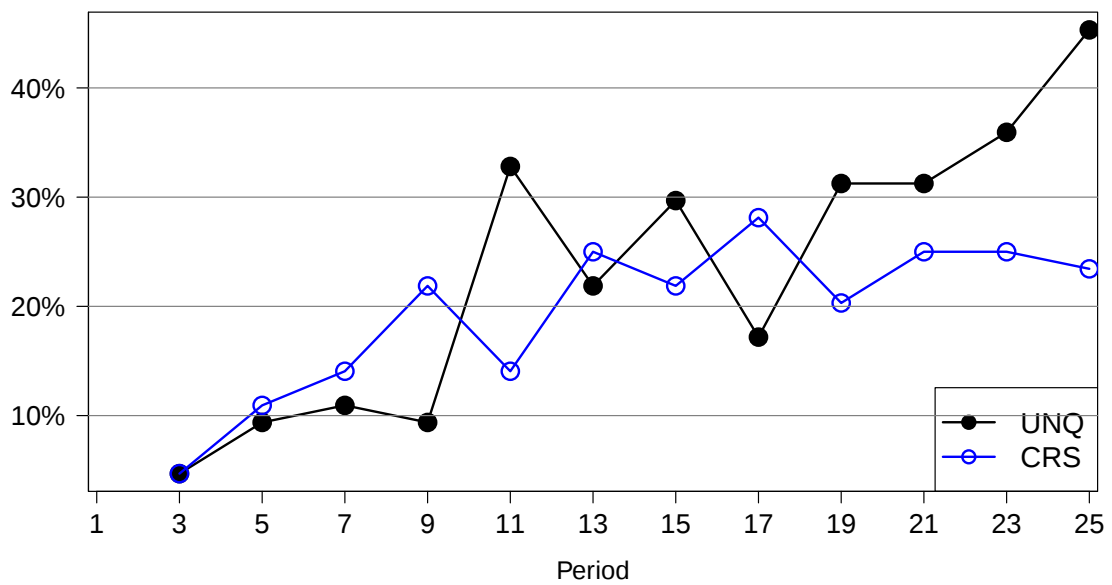


Figure 8: Proportion of best response investment decisions in each period.

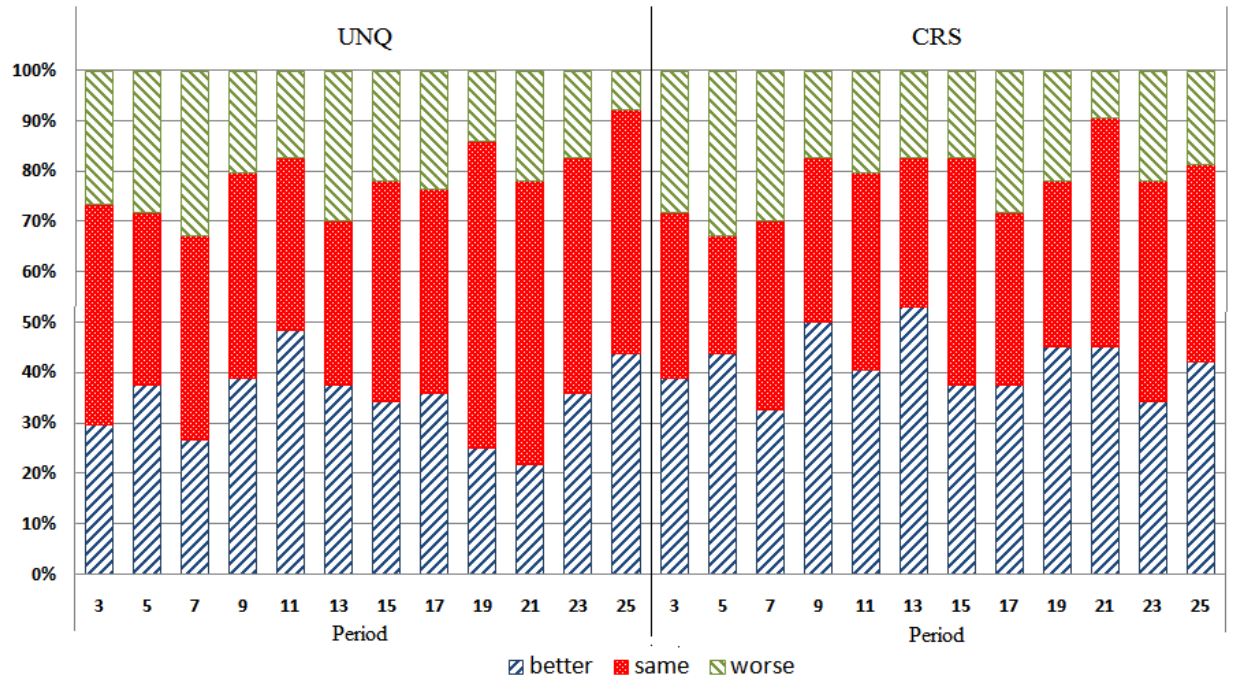


Figure 9: Proportions of better, same, and worse investment transitions

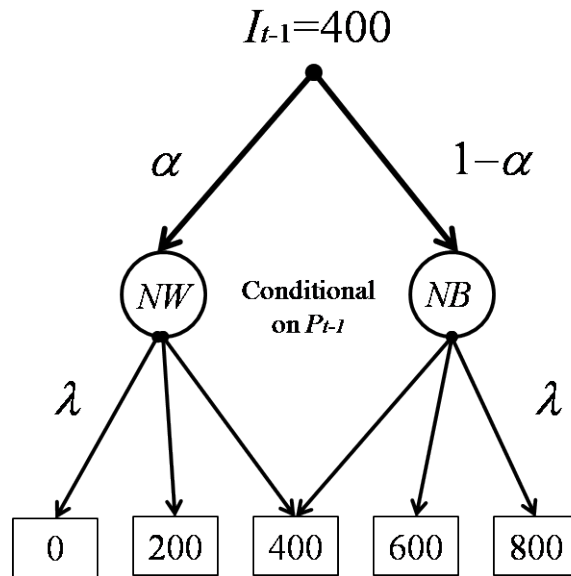


Figure 10: An example of the two stage determination of investment transition probability

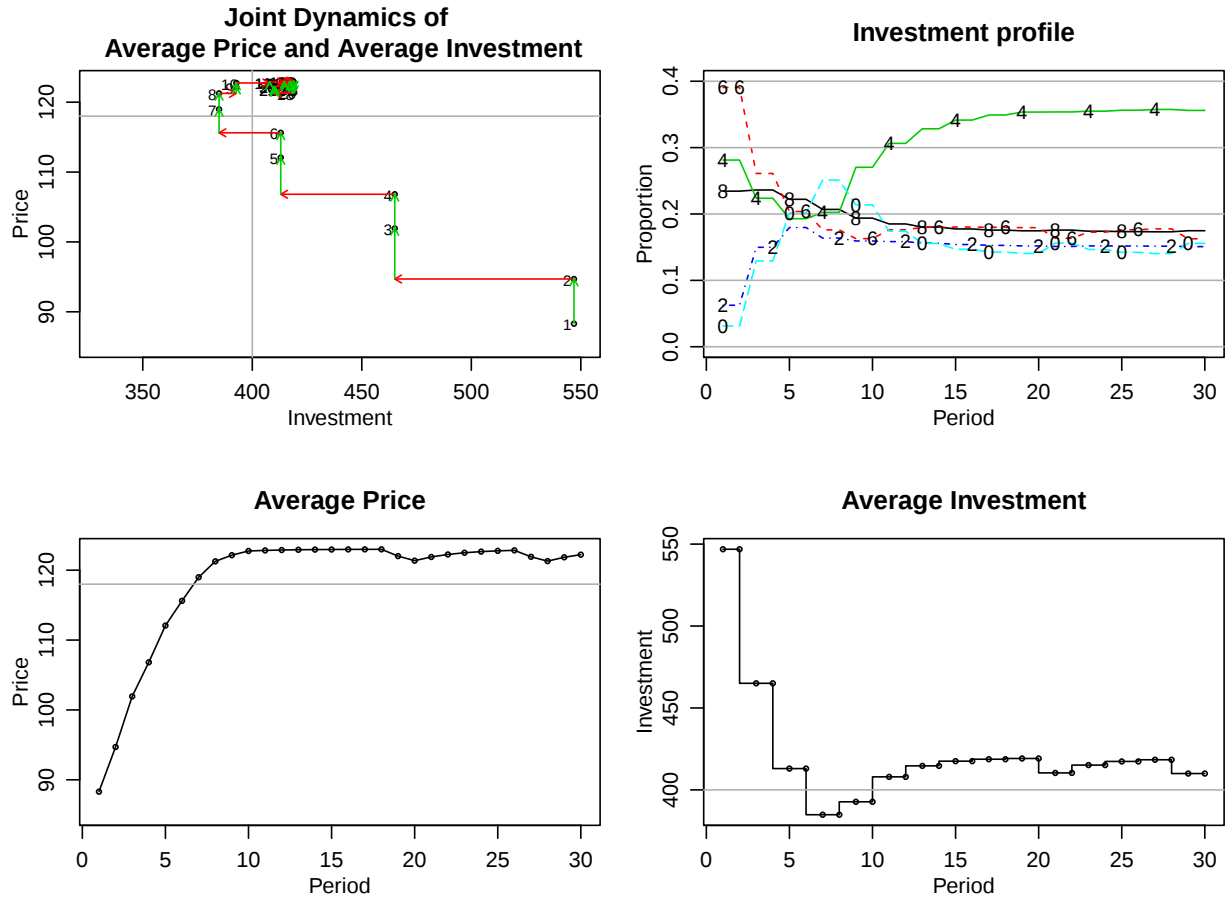


Figure 11: Expected dynamics under estimated price and investment dynamics models - UNQ treatment

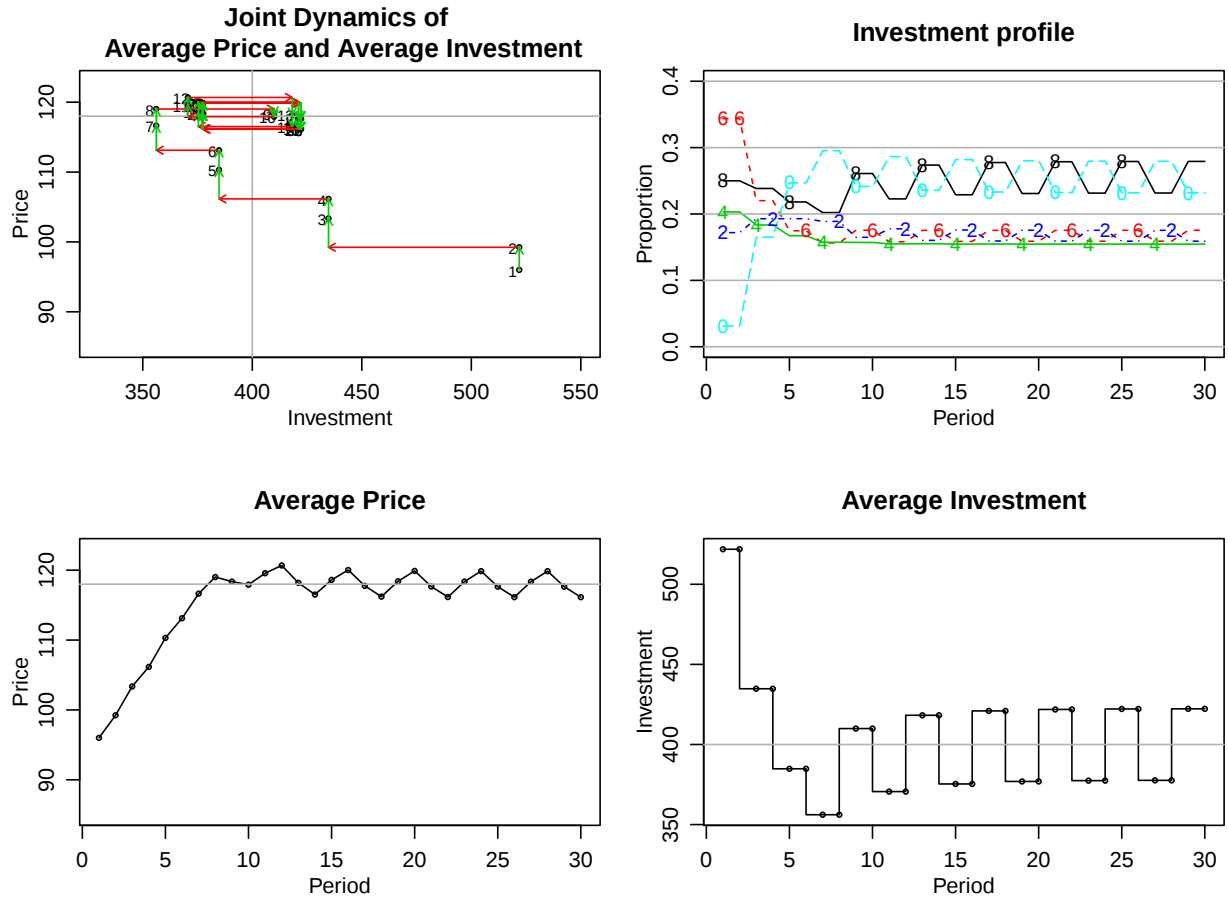


Figure 12: Expected dynamics under estimated price and investment dynamics models - CRS treatment