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An experiment on supply function competition

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ABSTRACT

We experimentally investigate key predictions of supply function equilibrium. While, overall, equilibrium organizes bidding behavior well, we observe three important deviations. First, bidding is sensitive to theoretically irrelevant changes of the demand distribution. Second, in a market with symmetric firms we observe tacit collusion in that firms provide less than the predicted quantities. Third, in a market with asymmetric capacities, the larger firm bids more competitively than predicted, while the smaller firms still provide less than equilibrium quantities.

1. Introduction

We experimentally investigate behavior in supply function competition that has first been modeled by Klemperer and Meyer (1989). Firms face uncertain demand and submit supply functions. The market clearing price is determined by the intersection of aggregate supply and (realized) demand. In its original formulation, the model has multiple equilibria with prices – roughly speaking – between the Cournot and the Bertrand equilibrium.

The most notable application of supply function equilibrium (SFE) analysis is spot market bidding in electricity markets, starting with Bolle (1992), Green and Newbery (1992) and Green (1996). In line with standard SFE models, rules of electricity spot markets typically require suppliers to offer a price schedule, with demand being uncertain. A variety of papers considered extensions of the original framework in order to capture more complexities inherent to many electricity markets, such as pivotal firms (Genc and Reynolds (2011)), cost asymmetries (Baldick et al. (2004), Baldick and Hogan (2002), Crawford et al. (2007)), entry (Green and Newbery (1992), Newbery (1998)), capacity constraints (Baldick et al. (2004), Holmberg (2007, 2008)), forward contracting (Newbery (1998)), and price caps (Baldick and Hogan (2002), Holmberg (2007, 2008)).

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Parallel to the theoretical progress, field studies on the performance of SFE accumulated. The evidence is, however, mixed. While some authors emphasize that SFE organizes actual electricity market experiences well – and better than Cournot models – (see Baldick et al. (2004) and the references cited therein) others are more critical with respect to behavioral assumptions and predictions (e.g., Sioshansi and Oren (2007), and the references cited therein). Hortacsu and Puller (2008) show in a study of the Texas electricity spot market that large firms behave close to the theoretical benchmark but small firms do not. According to Wolak (2003) the reason could be that small firms have less steps to play with and thus, the continuous supply function model might not be an appropriate approximation. In fact, he shows that when the discreteness of the offers is considered then the theoretical predictions cannot be rejected for the Australian market. However, there are often more constraints that complicate the direct applicability of the SFE approach to field data, such as non-convex costs, uncertainties on the supply side, transmission constraints, interaction with intra-day, reserve energy and forward markets, etc.

That said, the focus of our study is the potential role of behavioral complexities. While there is a large literature on the behavioral robustness of simple equilibria in quantities or prices (e.g., Holt (1995), and more recently Hinloopen and Normann (2009)), little is known about the potential role of behavior in an environment of supply function competition. Because our laboratory study seeks to fill this gap, we abstract away from the institutional and technical complexities mentioned above, that make it difficult to isolate behavioral phenomena in the field. Instead, we choose a set-up (with inelastic demand and a price cap) that yields unique equilibrium predictions in order to avoid non-equilibrium play due to coordination failure.

To our knowledge, only two experiments on supply function bidding have been previously conducted, both directly motivated by various phenomena in electricity spot markets. Interested in the role of forward markets, Brandts et al. (2008) studied both quantity and supply function competition with and without forward contracting. The introduction of a forward market increased total quantity produced and lowered prices paid by consumers. However, because there is a continuum of supply function equilibria in their set-up, supply functions, production levels and prices, as well as their shifts, could not be unambiguously derived from the SFE analysis. This reflects that identifying the predictive value of SFE bidding strategies was not the focus of their study.

More recently, and independently of our study, Brandts, Reynolds and Schram (2011), also investigate supply function equilibrium with inelastic demand and capacity constrained suppliers in an interesting laboratory study. Motivated by studies on market power in the electricity sector, they relate their results not only to SFE but also to a descriptive power index and to the predictions of a multi-unit auction model. While their multi-unit auction model yields unique symmetric equilibria in two of five treatments, here too, there is a range of SFE that makes it difficult to directly test the behavioral significance of the SFE model. The authors find that observed average market prices are consistent with the range of equilibria of the SFE model (and that the existence of pivotal suppliers increases the average market price). Behavior is inconsistent with the asymmetric equilibria of the multi-unit auction model in the three treatments where some suppliers are pivotal.

While these two other studies focus on potential electricity market applications (and are thus less concerned with uniqueness of predictions), our study is directed at the predictive power of SFE, and in particular includes testing two key predictions of SFE. First, we test the hypothesis that equilibrium supply functions are invariant to certain demand distribution parameters (which cannot be systematically varied in field studies). Second, we investigate how asymmetry of capacities affects the outcome of supply function competition. While some basic predictions of SFE are reflected in the data, we also find significant and systematic deviations from SFE. With symmetric competitors we find that bidding is on average less competitive than predicted by SFE. With one large and three small firms, only the small firms bid less than equilibrium quantities; the large firm provides higher than equilibrium quantities. We also find that firms react to theoretically irrelevant changes in the demand distribution; they bid less competitively in treatments where high demand realizations are more likely than low demand realizations.

Section 2 introduces the theoretical model underlying our analysis. In Section 3 we describe our experimental design and derive the central hypotheses. The results are reported in Section 4, and Section 5 concludes.

2. Theory and predictions

The theoretical framework of our experiment is a simplified version of a model by Holmberg (2007, 2008). The model deviates from more standard models of supply function competition by postulating inelastic demand and introducing a price cap and capacity constraints. This ensures existence and uniqueness of equilibrium without sacrificing some key characteristics of the SFE introduced by Klemperer and Meyer (1989), as we will explain below. Moreover, both the uniqueness of equilibria and the simplicity of the set-up make the model particularly suitable for experimental testing. Finally, inelastic demand, price caps and capacity constraints are characteristic features of many electricity exchanges, as e.g. discussed by Stoft (2002).[1]

[1] Inelastic demand is discussed on p. 43, price caps in chapter 2.4 (p. 140 ff.), and capacity constraints in the context of the description of marginal cost curves (p. 61, ff.).

Albeit we are aware of the limitations of our set-up in characterizing wholesale electricity markets, we believe its simplicity is rather its advantage. First, experimental evidence on supply function competition is scarce. Hence, for an initial study of the basic patterns of supply function bidding, a simple design seems more adequate. And second, it serves as an optimal departure point for future modifications that reflect more real characteristics of operating electricity markets.

In the model, n firms with constant marginal cost c compete in supply functions on a market with inelastic and uncertain demand ε and a price cap $\overline{p}$. Demand ε is distributed in $[\underline{\varepsilon}, \overline{\varepsilon}]$ with distribution $F(\varepsilon)$. We assume that the firms are capacity constrained and denote firm i's capacity by K_i. We assume that with positive probability the capacity constraints of all firms are binding, i.e. $\sum_{i=1}^{n} K_i \leq \overline{\varepsilon}$. The firms' bids consist of individual supply functions $S_i(p)$ that, for any given price, determine a quantity the firm is willing to offer.

Suppose firms are symmetric and have equal capacities denoted by $K_i = K$ for all i. It follows from Holmberg (2008) that the unique SFE yields the following aggregate inverse supply (see Appendix A),

$$p(\varepsilon) = c + \frac{\varepsilon^{n-1}}{(nK)^{n-1}}(\overline{p} - c) \quad \varepsilon \in [0, nK] \tag{1}$$

The first unit, at $\varepsilon = 0$, is offered at marginal cost. From there on, the markup increases in quantity. For the last unit a firm can supply, the highest possible price, $\overline{p}$, is posted.[2] Therefore the equilibrium price ultimately reaches the price cap at total maximum quantity, which in our experiment is equal to $\overline{\varepsilon}$. One particular interesting implication of equilibrium behavior is that bidding is independent of the distribution of demand, as long as the lower and the upper limits of the support remain unchanged – this is also a central feature of the Klemperer and Meyer (1989) model.[3]

Using the parameterization of our experimental treatment with symmetric firms (i.e., $n = 4$, $c = 0$, $\overline{p} = 50$, and $K_i = 30\ \forall_i$), the equilibrium bid function for ordinary firms (as opposed to large firms, whose behavior is analyzed next) is illustrated in Fig. 1.

Now suppose that there is one large firm, which has more capacity than the remaining $n-1$ firms (that have the same capacity). Denote an ordinary and the large firm's capacity constraint by K_l and K_h, respectively. Holmberg (2007) shows that in the unique SFE all firms' supply functions are identical in the range where none of them are capacity constrained (i.e. for quantities where $\varepsilon \in [0, nK_l]$). The large firm posts the price cap for all units it can supply in excess of the other $n-1$ ordinary firms. Consequently, the unique SFE yields the following aggregate inverse supply (see Appendix A),

$$p(\varepsilon) = \begin{cases} c + \frac{\varepsilon^{n-1}}{(nK_l)^{n-1}}(\overline{p} - c) & \varepsilon \in [0, nK_l] \\ \overline{p} & \varepsilon \in (nK_l, (n-1)K_l + K_h] \end{cases}$$

Most predictions from the symmetric model also apply here. For all quantities below K_l the individual supply functions of all firms (ordinary and large) coincide. For instance, the first unit is offered at marginal cost, and prices rise in the demanded quantity until they reach the price cap $\overline{p}$ at K_l. Quantities above K_l are offered at the price cap by the large firm. Note that in our experimental design we chose to introduce asymmetries by increasing the capacity of one firm (to 90 units), holding the other three firms' capacities constant (at 30 units, as in the symmetric treatments). Consequently, the equilibrium supply functions for the first 30 units of each firm are identical in the symmetric and the asymmetric treatments, which facilitate comparisons of bidding behavior across treatments.[4]

The additional insight of the asymmetric model is that, in equilibrium, the large firm does not undercut the ordinary firms' supply functions but rather drives prices to the maximum level in case demand turns out to be very high. We illustrate the equilibrium supply functions of large firms in Fig. 2 (for the parameterization we used in our experimental setting with asymmetric firms, i.e. $n = 4$, $K_l = 30$, $K_h = 90$, $c = 0$, and $\overline{p} = 50$; the supply functions of ordinary firms are as in Fig. 1 in this case).

3. Experimental design

The theoretical framework and analysis in Section 2 guided our experimental design described in this section. We run four treatments, T1–T4. In each treatment, an experimental market consists of four firms that face inelastic but uncertain demand. The price cap is set at 50 and marginal cost of all firms is zero. We compare a symmetric baseline market (T1) with two markets that exhibit different demand distributions (T2 and T3), and with another market that exhibits asymmetric (three ordinary and one large) firms (T4). More specifically

(T1) *Baseline treatment*: demand is distributed in the interval [1, 120], where each integer in this interval has the same probability. Each of the four firms has a capacity of 30 units.

[2] This prediction is due to the capacity constraint in Holmberg's model. Without that constraint, we obtain multiple equilibria, where the highest posted price is in between marginal cost (most competitive equilibrium) and the price cap; see Rudkevich et al. (1998) and Genc and Reynolds (2011).

[3] Other predictions include that equilibrium prices at each quantity decrease in the number of firms in the market (which is also predicted by Klemperer and Meyer (1989), and most other models of supply function competition), that equilibrium bids increase in the price cap, and that bids decrease if all firms' capacities increase.

[4] An alternative design choice would have been to hold total capacity constant across treatments and to adjust the distribution of capacity across firms. This, however, would have confronted the subjects with low capacities with a coarser grid (while the shape of the equilibrium supply functions derived in a continuous model would have been the same).

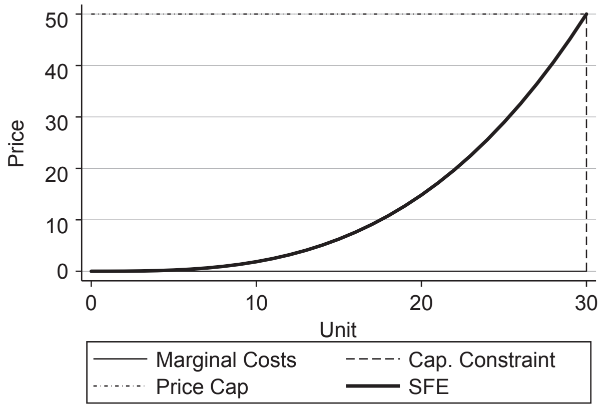

Fig. 1. Predicted supply function – ordinary firm.

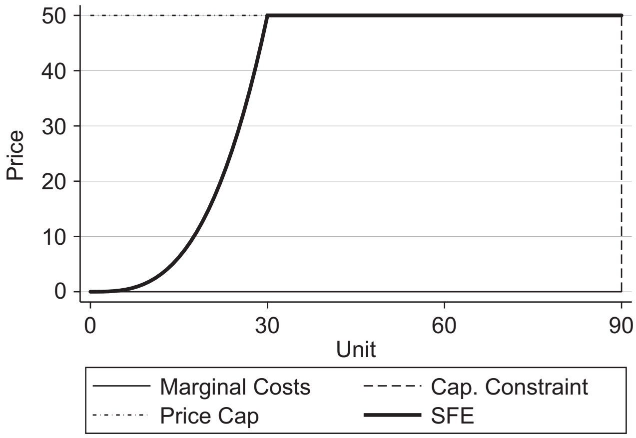

Fig. 2. Predicted supply function – large firm.

(T2) *Variation of the distribution I*: keeping everything else constant we change the demand distribution to a piecewise uniform distribution on the same support as in T1. In T2, demand comes from the interval [1, 80] with 50% probability and with the remaining 50% probability from the interval [81, 120], where each integer in the respective demand intervals is equally likely.

(T3) *Variation of the distribution II*: as in T2 we change the demand distribution to a piecewise uniform distribution, keeping everything else as in T1. In T3, demand comes from the interval [1, 80] with 10% probability and with the remaining 90% probability from the interval [81, 120], where each integer in the respective demand intervals is equally likely.

(T4) *Asymmetric firms*: keeping everything else as in the baseline treatment T1, we increase one firm's capacity from 30 to 90, and demand is distributed uniformly in the interval [1, 180].

Our null-hypotheses follow directly from the analysis in Section 2: ordinary firms in T1 and T4 bid as summarized in Fig. 1, and the large firm bids as summarized in Fig. 2. Moreover, Eq. (1) implies that bidding does not respond to the changes in the distribution of demand in T2 and T3; that is, bidders are predicted to submit the same supply function in treatments T1, T2, and T3.[5]

The experiment was conducted at the Cologne Laboratory for Experimental Research (CLER) in October 2006 and April 2013. A total of 180 undergraduate students in economics or business administration were recruited using ORSEE (Greiner (2004)) among the student population of the University of Cologne. Each student participated only in one of our treatments.

[5] In any empirical application of auction or oligopoly theory, demand is ultimately discrete, which is also true in our case. It is known that in such cases pure strategy equilibria may not exist. However, since the price and quantity grid is rather fine in our setting, we see the continuous model as an approximation, as it seems generally the case in the theoretical and empirical literature. In support of this, Holmberg et al. (2008) show that "if prices must be selected from a finite set the resulting step function converges to the continuous supply function as the number of steps increases". One implication of the discreteness is, though, that we needed to specify a rationing rule in case accumulated supply exceeds (realized) demand; we chose a proportional rationing rule (see Appendix B for details).

Subjects were randomly matched into groups of four, and each group formed one market in one of the four treatments. Anonymity was preserved in the sense that subjects never got to know the identity of the other subjects in their group. Each group remained together for 60 rounds.[6] In each round, each subject submitted a non-decreasing supply function via a computer interface.[7] Then demand was generated, each market was cleared, and feedback about the market outcome was distributed as described below.

Fig. 3 shows the interface that subjects saw on their screens.[8] Supply functions could be entered using the scrollbars located in the middle and submitted by pressing the button on the right. The numbers above the scrollbars indicated which price belonged to which unit. Each unit could be offered at a different price. Prices were exclusively integer values between 0 (marginal cost) and 50 (price cap). In addition, the supply function was drawn on the top part of the screen (see Appendix B for examples).

As soon as all supply functions were submitted, the computer generated the demand outcome, calculated the quantities and prices and showed them graphically to the subjects. More specifically, at the end of every round each subject received information about the group supply function (displayed graphically at the bottom of the screen), the demand realization, the market clearing price, own units sold, own profit and own accumulated profit (all shown in the top-left corner). The demand realization and the market clearing price were displayed graphically in the lower part of the screen together with the aggregate supply function. The market clearing price was depicted in the upper graph together with the individual supply function.

Prior to the experiment, each group played five dry runs that were not payoff relevant. Both, dry runs and payoff relevant rounds were always conducted within the same group, so that each group represents a statistically independent observation. Altogether, we collected 11/12/12/10 independent observations in treatment T1/T2/T3/T4.

All payments were made in experimental currency units (ECU) which were converted into Euro at a rate of 1/1100, 1/1500, 1/2700, and 1/2500 for T1, T2, T3, and T4, respectively.[9] The sessions lasted more than 1.5 h, but less than 2 h. Including a show-up fee of 2.5 Euros, average gains (standard deviation) were 21.58 (6.92) Euros in T1, 23.88 (4.4) Euros in T2, 21.88 (3.45) Euros in T3, and 17.18 (6.52) and 29.27 (10.55) Euros in T4 for ordinary and large firms.[10]

4. Results

Fig. 4 summarizes the bidding behavior in our four treatments. Each of the five graphs shows the actual average supply function of each individual market in the respective treatment (thin, dashed lines), an estimate of the corresponding overall average supply function (thick dashed line) along with a 95% confidence interval around that estimate (shaded area), and finally the predicted SFE behavior (thick, continuous line).[11] Fig. 4(a) shows the supply of ordinary firms in treatments T1–T4, Fig. 4(b) shows the supply for the large firm in treatment T4.

In line with SFE predictions, the figures show that, on average, firms offer the first unit at prices close to marginal cost, additional units at (mostly convexly) increasing prices, and ask for prices close to the maximum possible price at the maximum capacity. These patterns support what might be interpreted as the central qualitative prediction of SFE: higher demand is accompanied by increasing mark-ups. Naively bidding a constant markup on (marginal) costs would have just led to a constant bid function.

That said, the figures also reveal important and systematic quantitative deviations from SFE. In particular, while there is considerable heterogeneity across markets, consistent with the results in Brandts et al. (2011),[12] the estimated average supply functions of ordinary firms in T1–T4 tend to be less competitive than predicted in almost the whole price-range (only for very small and very large prices is the SFE prediction within the 95% confidence interval of our estimate). In stark contrast, large firms bid less competitively than predicted only at small prices, yet generally (for prices above 10) bid more aggressively than predicted.

Comparing the bid functions across different demand conditions in T1–T3, we also find that, unlike predicted by SFE, firms behave more competitively if there is more weight on low demand realizations. Fig. 5 illustrates this by plotting the estimated average supply function in the respective treatments along with a 95% confidence interval around that estimate

[6] Repetition does not change our null-hypotheses because the finiteness of the game was commonly known and because of the uniqueness of the one-shot equilibrium; at the same time, feedback across rounds may facilitate learning and help subjects converge to an equilibrium.

[7] In real electricity markets, firms submit non-decreasing supply functions as well since a bid must be placed for each unit.

[8] All expressions are translated from German. For T4, the screen design was slightly different, specifically depending on the firm type. Screenshots of the treatment can be found in Appendix C. The experimental software was developed in Visual Basic.

[9] The exchange rates were different for the different treatments since expected payments in ECU differed across treatments. Prior to the experiment we ran a pilot session of T4 in order to adjust conversion rates and to decide on details of the design such as the decision time to give the subjects in each round. No data of this session was used in our analysis. However, results do not change when including the data.

[10] The equivalent values in US dollars for the average gains are 27.2 in T1, 31.12 in T2, 28.51 in T3, and 21.65 for ordinary and 36.89 for large firms in T4. The values are calculated using an average exchange rate of the days, when the sessions took place.

[11] Each estimate is based on a non-parametric Gaussian kernel and a local polynomial regression estimator of order 2; the bandwidth is selected using the rule-of-thumb (see e.g. Li and Racine (2007, Ch. 2)). Actual overall averages do not much differ from estimated averages, but, as is obvious from looking at individual market data in Fig. 4, the confidence interval of the actual average curve will be larger than the confidence interval of the estimated curve of averages.

[12] Brandts et al. report group average prices (instead of average SF), for all rounds and for the last five, also revealing considerable heterogeneity within treatments.

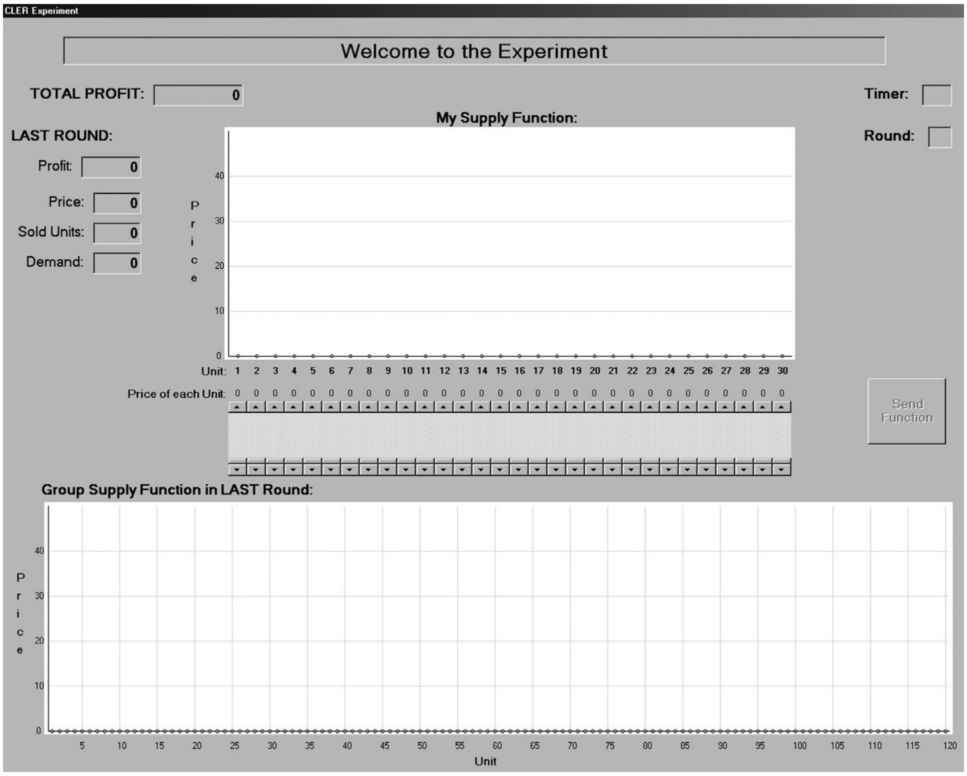

Fig. 3. Screenshot of entry mask.

(shaded area) for T1/T2/T3 (left part of the figure), as well as for ordinary firms in T1 and T4 (right part). Only at prices 0 and 1 and in the interval [29,50] (or [37,50], respectively), we cannot reject the hypothesis that the estimated averages in T1 and T2 (or T3, respectively) are equal. A lack of disciplining market feedback for lower quantities may have fostered withholding of supply. The effect is the stronger the less likely low demand scenarios are.[13] Note that theory would predict identical bidding behavior in T1–T3, which is clearly inconsistent with our data.

The right-hand part of Fig. 5 compares behavior of ordinary bidders in T1 and T4. In this case we cannot identify differences in bidding behavior, which is consistent with the theoretical prediction. Recall, however, that in T4 bidding behavior of large firms is much more competitive than theory would predict. A comparison of aggregate bidding behavior in T1 and T4 (see Fig. 6) shows that aggregate supply is larger in T4 than in T1 at all price levels above 16. The effect is due to the rather competitive bidding of large firms. In fact ordinary firms' aggregate supply is even slightly (but insignificantly, see Fig. 5) lower in T4 than in T1 at all prices. Clearly, large firms do not exploit their price setting power as predicted by theory; starting at low prices, they rather increase their market shares above what is expected by SFE, probably in an attempt to win a share that reflects more accurately their share of total capacity.[14]

Fig. 7 closes the results section by showing that there is no systematic dynamic time trend in bidding behavior. More specifically, we calculate "Distance to SFE" by summing up bid over all groups and all prices in a certain round and subtracting the sum of the equilibrium quantities (again over all groups and prices). This gives a measure of how close the observed market performance comes to the equilibrium prediction on average. The figure shows that deviations from SFE are rather constant over time in T1–T3, while they non-monotonically fluctuate in T4. There appears to be no systematic time trend, such as convergence to SFE. For instance, seven groups in T1 and T2 and eight groups in T3 moved somewhat closer to SFE from the first to the last quarter of the experiment, while four/five/four groups in T1/T2/T3, respectively, moved somewhat away. T4 shows a similar pattern, having half of the groups moving closer while the other half move away from SFE.

[13] We note that behavior in our treatment T3 with a probability of 10% for realizations from [1,80] is basically the same as behavior in another treatment that we conducted where the probability of those demand realizations is zero. We do not further report results of this treatment here, though, because zero probability allows for multiple equilibria.

[14] We can reject both, the hypothesis that the average market share (over 60 rounds) of large firms equals the theoretically predicted market share of 29%, as well as the hypothesis that it equals 50%, which is the large firms' share of total capacity (Wilcoxon signed-rank tests, $p=0.0069$ and $p=0.0051$, respectively).

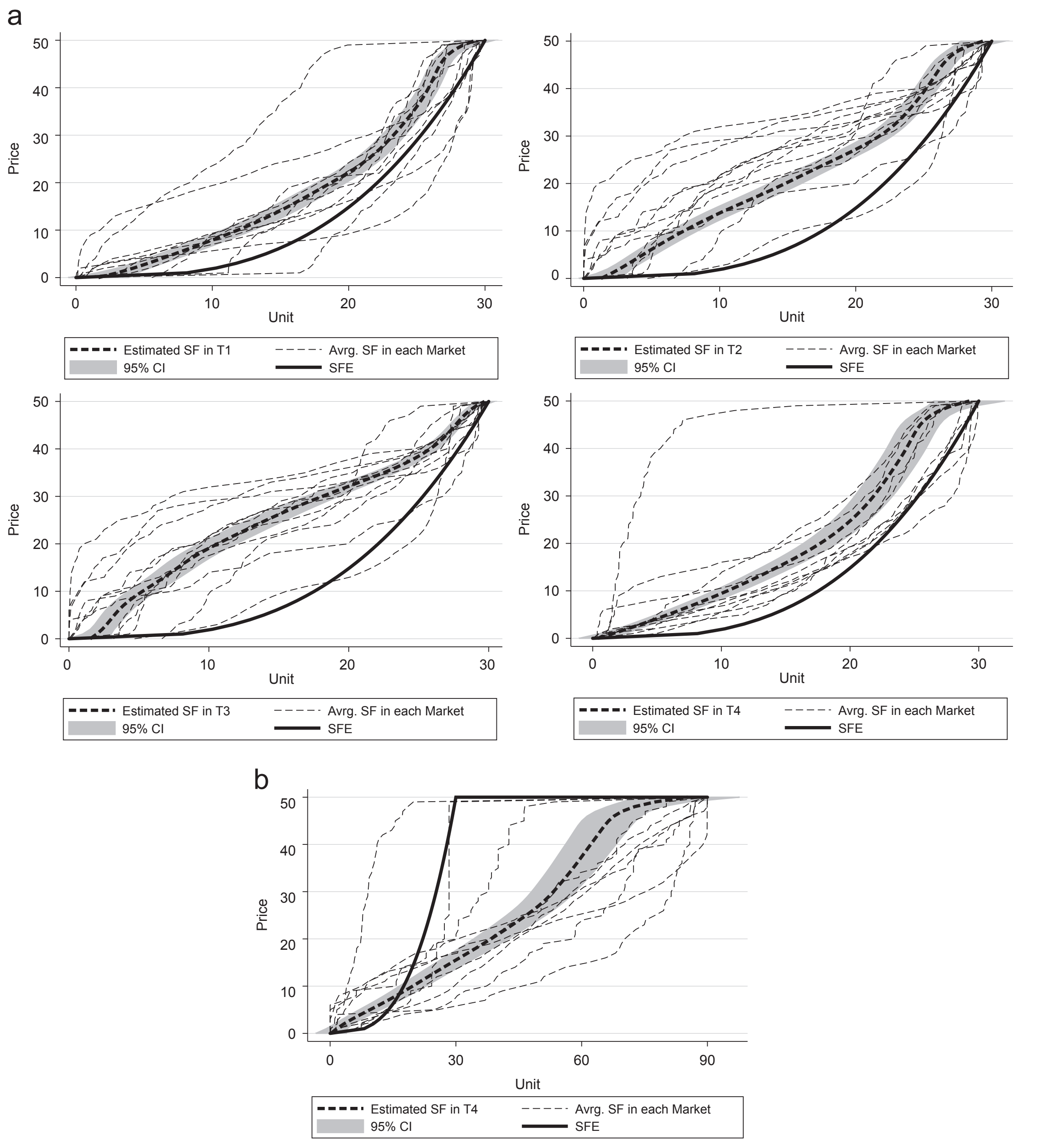

Fig. 4. Estimated and predicted supply functions. (a) Estimated and predicted supply functions in T1 (upper left), T2 (upper right), T3 (lower left), and T4 (lower right). (b) Estimated and predicted supply function of large players in T4.

5. Discussion and conclusion

We conducted the first behavioral robustness check of SFE, testing key predictions of supply function competition in a framework with unique equilibrium predictions. Overall, SFE organizes bidding behavior well. The shapes of the supply functions (increasing and mostly convex) are qualitatively in line with what is predicted by SFE. However, symmetric firms and small firms in an asymmetric case provide smaller quantities than predicted by SFE, while the large firm in our asymmetric case behaves (for larger prices) more competitively than SFE suggests. We also find that demand uncertainty matters in ways not captured by SFE.

In our experiment outcomes tend to be somewhat less competitive than theoretically expected. Laboratory supply function competition allows us to additionally observe that the effect is strongest for low prices and for outcomes that are unlikely to occur – that is, when the incentive to outbid others is rather small. Our observations are in line with part of the

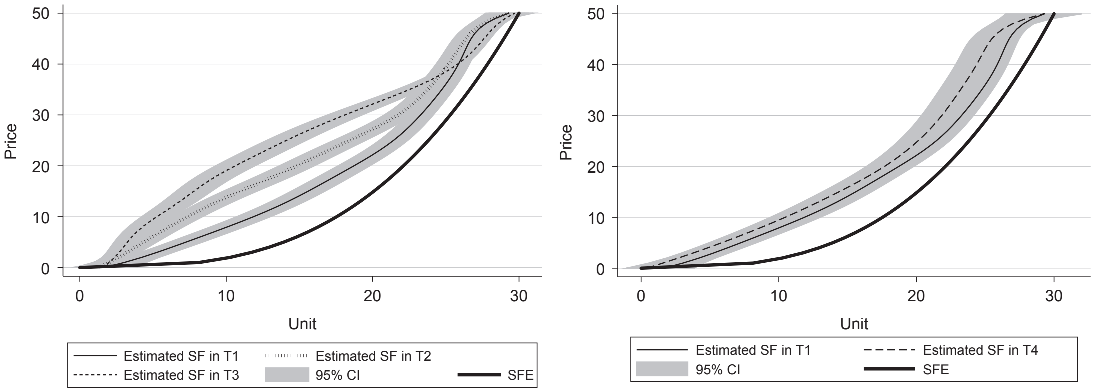

Fig. 5. Comparison of estimated supply function of ordinary firms across T1–T3 (left), and across T1 and T4 (right).

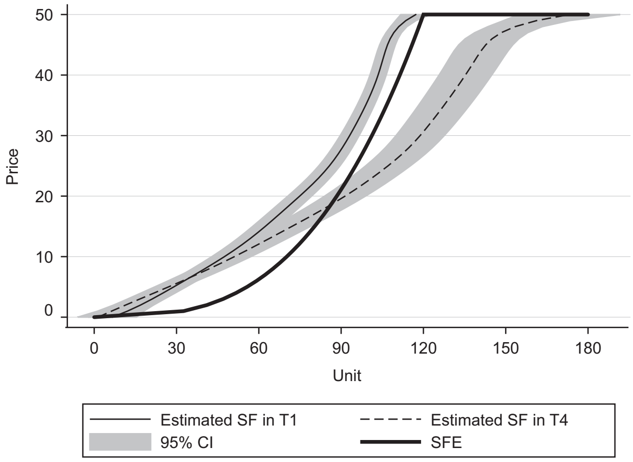

Fig. 6. Estimated group supply functions in T1 and T4.

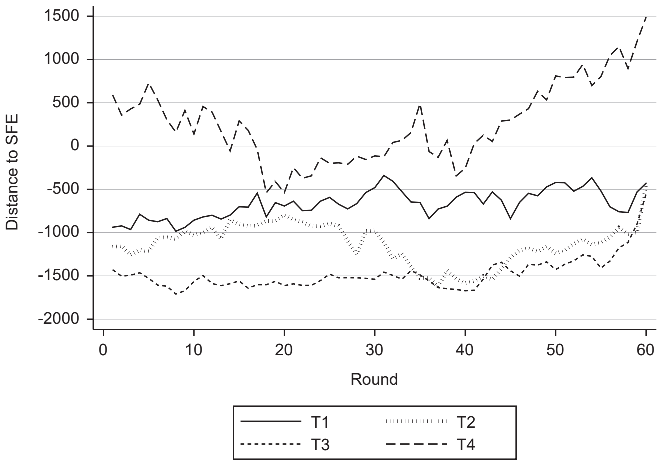

Fig. 7. Average distance to SFE.

experimental literature on pure quantity and pure price competition: in several studies outcomes tend to be somewhat less competitive than theoretically expected (see Holt (1995), the meta study in Huck et al. (2004), and Hinloopen and Normann (2009)).

While we caution that our study was conducted with students in a highly abstract environment, we note that our findings also seem consistent with some of the phenomena observed in the field. For one, we find that the demand distribution matters when it should not: less demand uncertainty (in the sense that low demand becomes less likely) makes it easier for firms to reach collusive outcomes. This seems to 'behaviorally' reinforce the robustness of earlier findings from field studies (see Baldick and Hogan (2002) for an analysis of electricity supply in the England and Wales market in 1999) and from experiments with 'adaptive agents' simulating the behavior of oligopolistic electricity generators (see Bower and Bunn (2001)) that requiring supply functions to remain fixed over an extended time horizon such that there is a larger variation in demand reduces the incentive and capability to mark up prices. Second, we find that (with unequal firm sizes) large firms generally fail to fully exploit their market power. This suggests that bounded rationality might also contribute to the observation that prices are sometimes below what can be expected from strategic modeling.[15]

Our laboratory environment is held simple in order to provide a first test whether SFE can in principle organize bidding behavior. Like in theoretical work, our conclusions are conditional on our framework. The next step would be to check the robustness of our results in more complex environments, similar to what has been done in the already mature literature on laboratory quantity and price competition. Because the typical application of SFE is the electricity spot market, and electricity generation is plagued by non-standard costs (Stoft, 2002), we think that promising extensions will include variations in the cost structure such as increasing marginal costs, investment and fixed costs, cost asymmetries, and non-convex costs. Also, controlled laboratory research might help to separate competing (behavioral and institutional) explanations for some field data phenomena not easily predicted by SFE, as they are discussed in the theoretical and empirical literature. That said, we hypothesize, given the success of the simple SFE model in organizing central bidding patterns that SFE will prove to be a behaviorally useful benchmark in more complex environments.

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Appendix A. Equilibrium predictions

This section sketches how the supply function equilibrium can be derived for our experimental markets. Exact proofs are found in Holmberg (2007, 2008).

We consider a market with n firms with constant marginal costs c. Bids submitted by each firm are piecewise twice continuously differentiable and non-decreasing supply functions $S_i(\mathrm{p})$, where p is the price. $S_{-i}(p)$ represents the aggregate supply of the competitors of firm i, and $S(p)$ the total supply. Demand ε is perfectly inelastic. Its density function $f(\varepsilon)$ is continuously differentiable and has a convex support set with $f(\varepsilon)>0$. When maximizing the expected profit in response to $S_{-i}(p)$ on an interval $[\mu,\nu]$ where $S_{-i}(p)$ is differentiable, player i faces a degenerate control problem.

$$\max_{p(\varepsilon)} \int_{\mu}^{\nu} [\varepsilon - S_{-i}(p(\varepsilon))](p(\varepsilon)-c)f(\varepsilon)\, d\varepsilon$$

It is degenerate because $p' = dp/d\varepsilon$ does not enter the goal function. If i can use only non-decreasing supply functions, $p(\varepsilon)$ has to obey the restriction $p' = (\varepsilon) \le 1/S'_{-i}(p)$. This restriction holds in the equilibria derived below. Under such conditions, i maximizes the expected profit by choosing the optimal $p(\varepsilon)$ for all ε separately. The respective first order condition is

$$[\varepsilon - S_{-i}(p(\varepsilon)) - S'_{-i}(p(\varepsilon)) \cdot (P(\varepsilon)-c)]f(\varepsilon) = 0 \tag{2}$$

Eq. (2) provides us with a system of n differential equations for the n supply functions $S_i(p)$. Taking $S_i(p) = \varepsilon - S_{-i}(p)$ into account, a symmetric SFE has to satisfy the following system of differential equations

$$S_i(p) - (n-1)S'_i(p)(p-c) = 0, \quad i = 1, \ldots, n \tag{3}$$

The general solution of Eq. (3) is

$$S_i(p) = a(p-c)^{1/(n-1)}, \quad a = const > 0 \tag{4}$$

[15] See Wolfram (1999). Also, the study by London Economics (2007) on behalf of the European Commission indicates 'too little' exploitation of market power of pivotal firms: e.g., for 2005, the largest supplier in Germany was calculated to be pivotal in more than 50% of all hours, but price mark-ups on short run marginal costs were computed to be 15.2%, which appears too low given the strong pivotalness. The result is also in accordance with Mason et al. (1992) who found Cournot markets with asymmetric firms to be more competitive than markets with symmetric (equal costs) firms.

which implies the inverse market supply function

$$p(\varepsilon) = c + \left(\frac{\varepsilon}{na}\right)^{n-1} \tag{5}$$

a is an arbitrary positive parameter which allows for a continuum of equilibria.

The only asymmetric solutions of Eq. (2) are (see Bolle (1992), Genc and Reynolds (2011), and Holmberg (2007))

$$S_i(p) = a(p-c)^{1/(n-1)} + b_i/(p-c) \text{ with } \sum_{i=1}^{n} b_i = 0. \tag{6}$$

These solutions violate monotonicity of supply functions when prices are close to marginal costs. However, aggregate supply has the same functional form as in symmetric SFE.

In case there are a price cap $\overline{p}$ and capacity constraints $K_1 \le K_2 \le \ldots \le K_n$ that become binding with positive probability, Holmberg (2007, 2008) shows that there is a unique equilibrium with identical bids as long as aggregate demand is smaller than or equal to $\varepsilon^* = \sum_{i=1}^{n-1} K_i + K_{n-1}$. If $p = \overline{p}$, any demand ε with $\varepsilon^* \le \varepsilon \le \sum_{i=1}^{n} K_i$ is supplied.

Treatments T1–T3 (Four firms with equal capacities $\overline{\varepsilon}_i = 3c$ and marginal cost $c=0$, and demand is uniformly distributed or piecewise uniformly distributed on [1, 120]): The unique SFE is described by Eqs. (4) and (5).[16]

$$S_i(p) = 30\left(\frac{p}{\overline{p}}\right)^{1/3} \tag{7}$$

The inverse aggregate supply function is

$$p(\varepsilon) = \overline{p}\left(\frac{\varepsilon}{120}\right)^{3}. \tag{8}$$

Asymmetric equilibria are excluded by Holmberg (2007).

Treatment T4 (Three firms have a capacity of 30, the fourth firm has a capacity of 90, and demand is uniformly distributed on [1, 180]): Eqs. (7) and (8) describe the market up to $\overline{p}$ where $\varepsilon^* = 120$ is supplied (or more if demand is higher). Beyond 120, additional demand is supplied only by the large firm. This equilibrium is unique according to Holmberg (2007).

Appendix B. Instructions

In the following, we provide the instructions for T1. The instructions for T2 and T3 are identical except for the demand interval used. In T4 the instructions are slightly adjusted in order to account for the asymmetry of the market configuration. All instructions are translated from German.

Instructions

Welcome to the experiment and thank you for participating. Please read the instructions carefully. They are identical for all participants.

If you have any questions, please raise your hand. An experimenter will then come to you. From now on any communication among the participants is forbidden. In case you do not adhere to this rule, you will be excluded from the experiment and the payout. Please switch off your mobile phone now.

During the experiment all monetary amounts are indicated in ECU (Experimental Currency Units). The conversion rate 1€=1100 ECU is used to calculate the payout at the end of the experiment. You get 2.50€ for participating and can earn a higher amount in the course of the experiment. How much you will earn in total depends on your decisions and those of the other participants. All your decisions are confidential.

Making the decision

You compete with three other participants as suppliers in a market. You and the other participants act as producers who make decisions about the supply of a fictitious good. The demand for that good is simulated by the computer. Your profit depends on your supply decision, the supply decisions of the other three producers in your market, and the simulated demand.

The experiment has several rounds. In every single round you and the other producers have to make new supply decisions while the computer determines a new demand realization. The same four producers stay together throughout the whole experiment. The identities of the other producers, however, are not disclosed at any time.

At the beginning of the experiment you and the other producers in your market will play 5 training rounds that do *not* count for the final payout. Here you can test different behaviors. After that you will play 60 rounds that do count for the final payout.

[16] Holmberg's (2007) proof requires only that demand in [ε*-μ, ε*]occurs with a positive probability for all positive μ.

Demand

Every round the computer buys between 1 and 120 units of the good that you and the other producers in your market supply. In each round the demand realization is generated randomly. All quantities between 1 and 120 have the same probability.

The computer pays the same *market price* for all units bought. This price is determined by the intersection between supply and demand, as we will explain later on. The computer will never pay a price higher than 50 ECU per unit.

Decisions about supply

In each round you and the other producers in the market can produce a maximum of 30 units of the good. There are no costs of production.

In each round you have to indicate for each of the 30 units the minimum price you are willing to accept. Different prices can be assigned to different units. The price assigned to a certain unit cannot be lower than the one chosen for the previous unit. For instance, if you choose a price of 10 ECU for the fourth unit, you have to assign at least a price equal to 10 ECU to the fifth unit. However, the price for the fifth unit can also be higher than 10 ECU.

A unit will only be sold if the price you ask for is equal to or smaller than the market price. We will show later how the market price is calculated.

You are not allowed to ask for a price higher than 50 ECU, since the computer does not pay a price higher than that.

How do I submit the supply function?

In each round you see the entry mask as shown above, which you can also see right now on your screen. Use the top part of the screen to indicate your supply. You can choose the minimum selling prices by using the scroll bars below the diagram in the upper part of the screen. You can raise the price by clicking the top arrow, and lower it by clicking the bottom arrow. If you raise the price for a unit, the prices for the following units will be adjusted automatically to at least that level. The reason is that for any of those units you have to ask as least as much as for the previous units. You can now test this on your computer.

In every round the supply decision from the previous round is adopted as start position for the next round. However, prices can always be modified for as many units as you want.

The market price

Once the four producers have chosen their minimum selling prices for all 30 units (= their individual supply curves), the computer adds up individual supplies at each price. The result is the *aggregate supply curve* of the market in that particular round. In the following figure we illustrate with an example how the aggregate supply curve is determined. You can see the four entry screens with four individual supply curves. They are chosen arbitrarily to illustrate the spectrum of possibilities. On the screen showing the supply curve of all producers you can see the resulting aggregated supply function.

Suppose, for example, the price is 20, and the first (second, third, fourth) producer is willing to supply 2 (27, 30, 9) units according to their supply decisions. Then, aggregate supply equals 2+27+30+9 = 68 at a price of 20.

The intersection of the aggregate supply curve and the demand realization (between 0 and 120) determines the market price and the number of units sold at this price. All units offered at minimum prices lower than the market price are sold at the market price. **The market price is equal to the highest minimum selling price at which the computer buys.**

The following graphic shows an example. You can see the aggregate supply curve of the market. Furthermore, you see that the demand realization is 90 units in this round. In the example, the minimum price for the 90th unit, according to the aggregate supply curve, is 40 ECU. Consequently, this is also the market price that is paid for all 90 units sold.

You will always sell all units that you have offered at a price strictly lower than the market price. However, it may occur that a firm does not sell units which it has offered at a price *equal to* the market price. This happens whenever multiple units have been supplied at the market price, but the computer does not buy all of them. In this case ‘proportional rationing’ is used. The following example makes clear how the rationing rule works.

Example: Suppose that demand is 20 units and the market price is 25 ECU. 19 units are being offered at a price lower than 25 ECU, and 4 units at exactly 25 ECU (The minimum selling price for the rest of the units is higher than 25 ECU.). Suppose you have offered one unit at a price equal to 25 ECU and 7 units at a lower price. Then you will sell the 7 units that you have offered at a price lower than 25 ECU in any case. However, out of the 4 units offered at exactly 25 ECU, only one unit will be bought by the computer, since it will buy no more than 20 units, and 19 units were already offered at prices less than 25 ECU. You have a share of 25% in the units offered exactly at the market price. Thus, you will supply 1/4 of the demand of one unit that still has to be satisfied. You therefore sell 7.25 units at a market price equal to 25 ECU. Your profit is hence 7.25 × 25 ECU = 181.25 ECU.

Feedback

At the end of each round you obtain the following information:

- the demand of the computer;
- the market price;
- the number of units that you have sold;
- your profit in the current round;
- your total profit up to the current round.

In addition, you also see a graphic containing the following information:

- the aggregate supply curve;
- the demand;
- the market price.

The training periods

Before the experiment begins, you will practice during 5 rounds with the other 3 firms in your market to get used to the software. The profits from these training periods are not being paid out. When the training periods are over, the system will be reset, and the experimental rounds relevant for the final payout begin.

See Appendix Figs. B1–B7

Appendix C. Screenshots of T4

See Appendix Figs. C8 and 9.

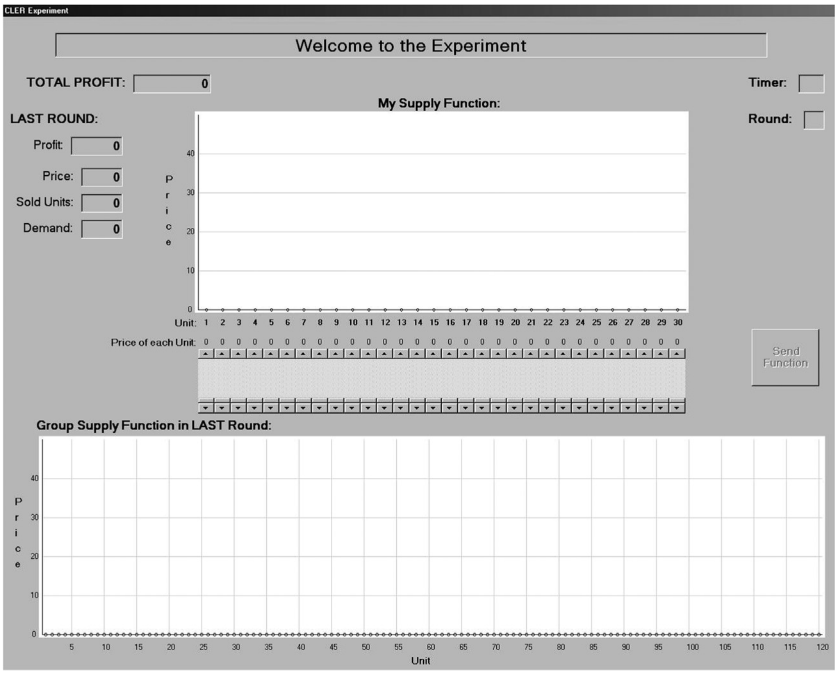

Fig. B1. Entry mask.

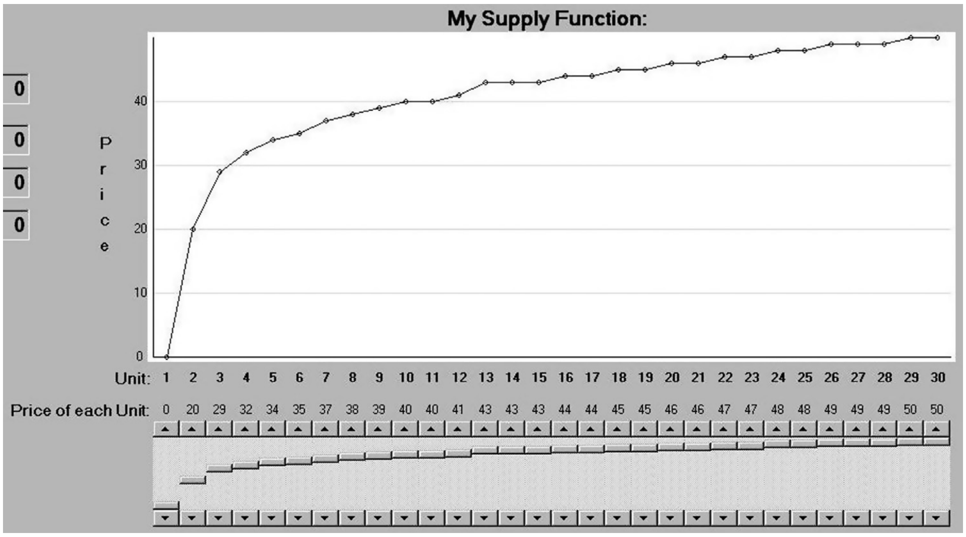

Fig. B2. Producer 1.

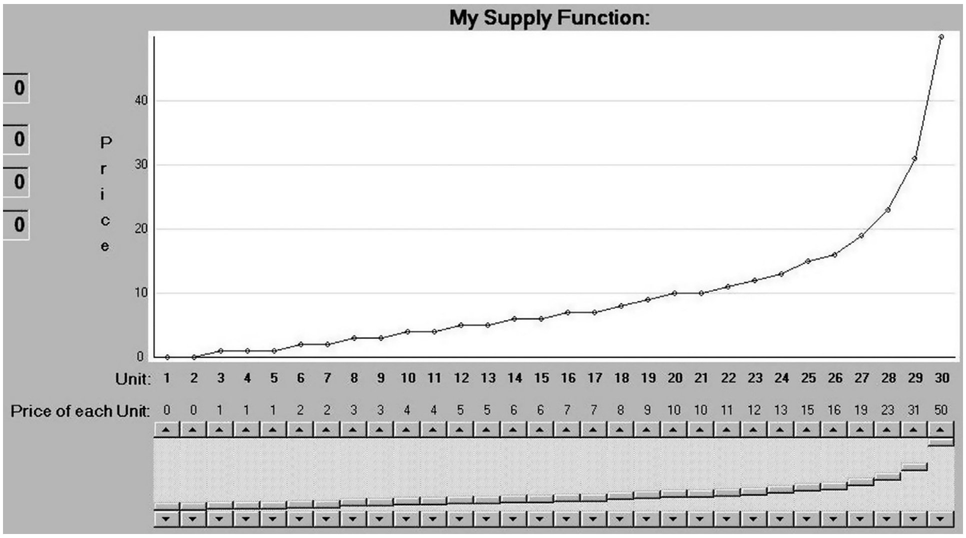

Fig. B3. Producer 2.

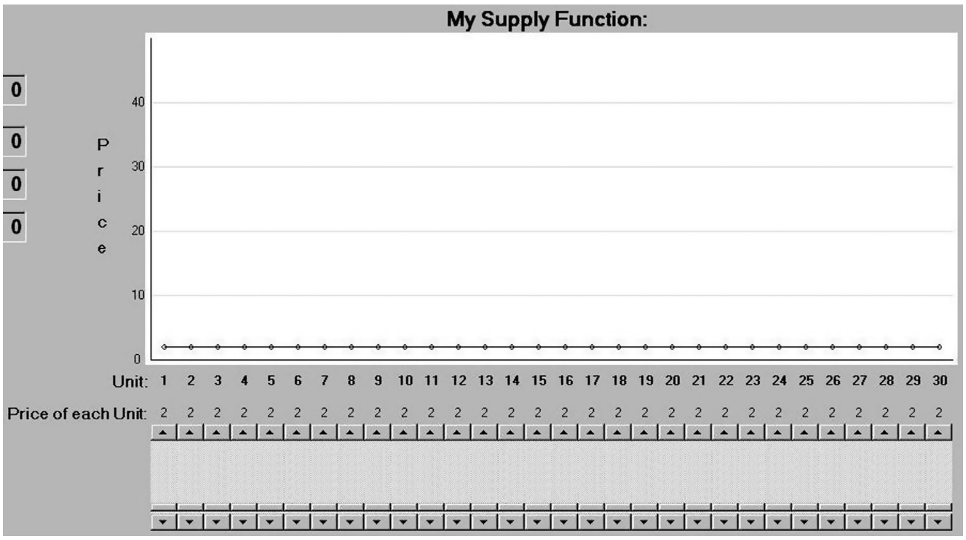

Fig. B4. Producer 3.

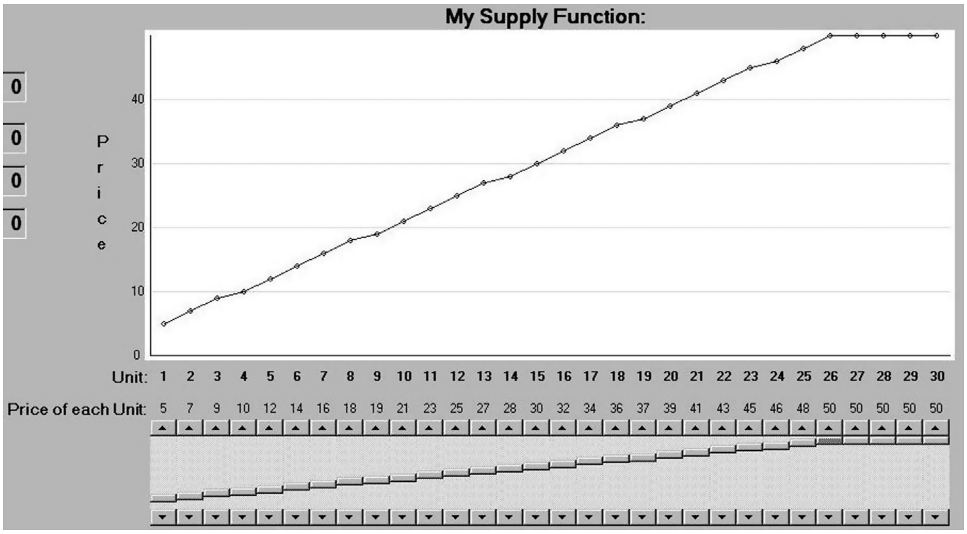

Fig. B5. Producer 4.

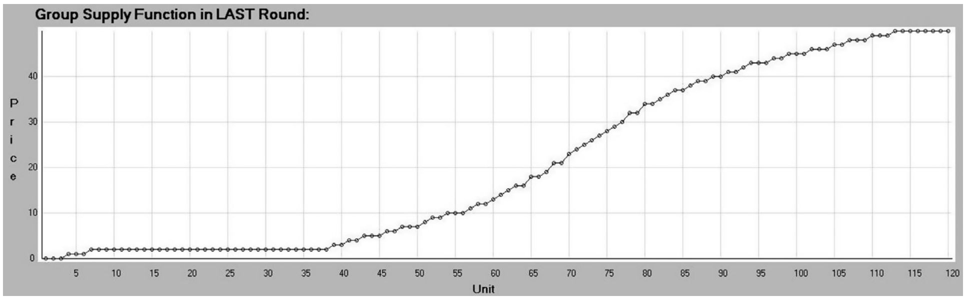

Fig. B6. Supply curve of all producers.

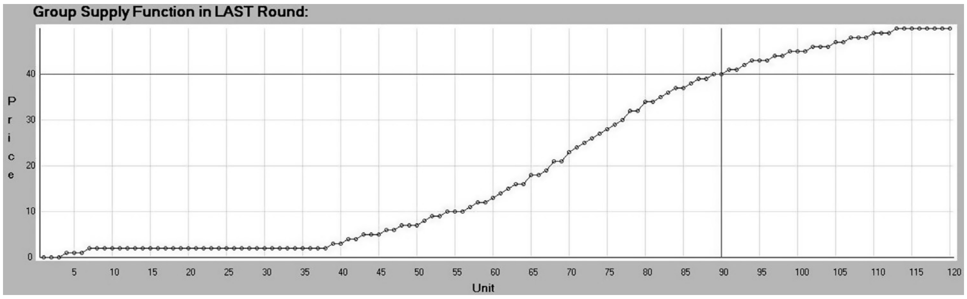

Fig. B7. Supply function, demand market price.

Appendix D. Supplementary materials

Supplementary materials associated with this article can be found in the online version at http://dx.doi.org/10.1016/j.euroecorev.2013.06.006.

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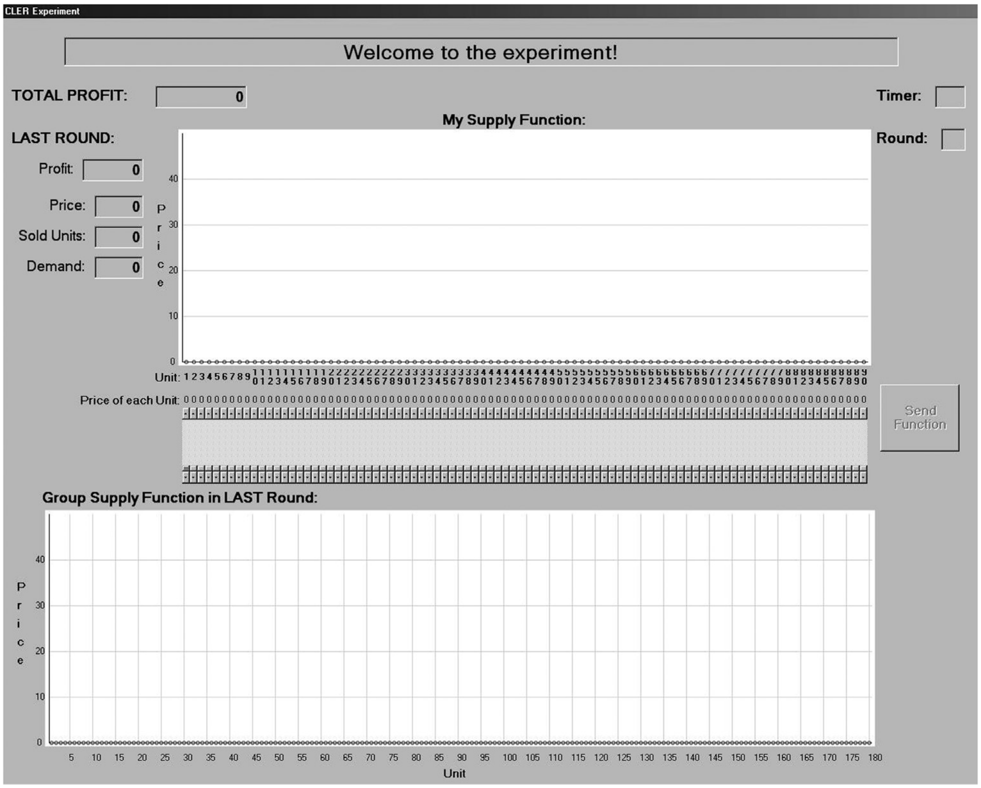

Fig. C8. Lagre firm.

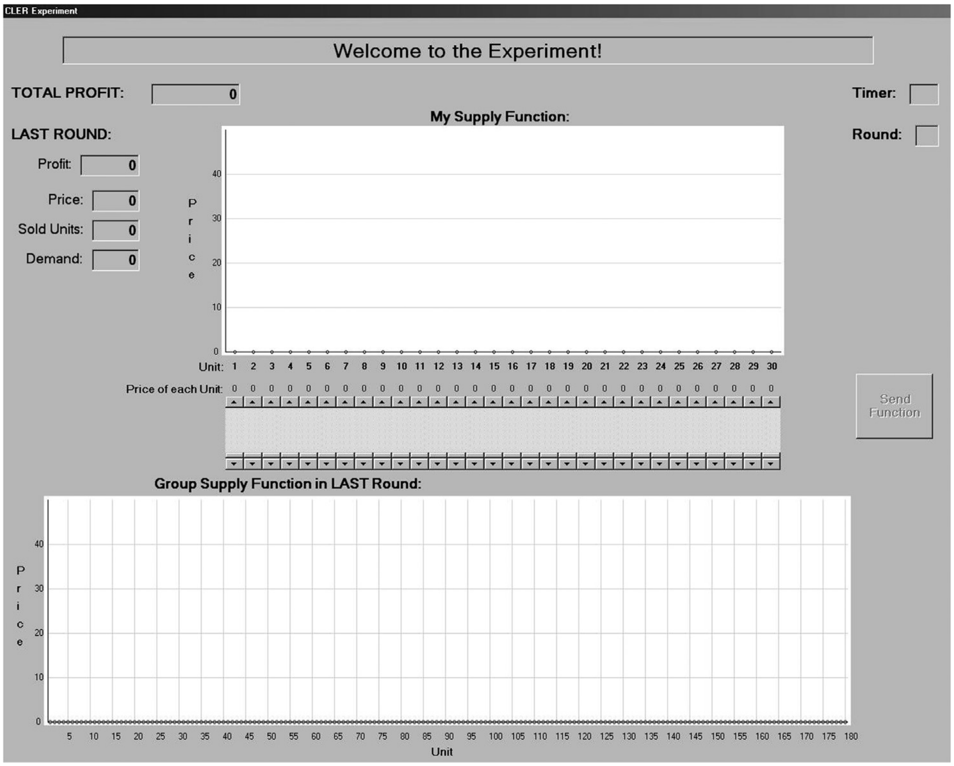

Fig. C9. Ordinary firm.

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