

# ONLINE APPENDICES

## Appendix A

### Solving for MPE equilibria

We express the equilibrium as a system of equations in terms of choice continuation values. Denote the per period profits by  $\Pi^\alpha(\mathbf{s}_t)$  and let  $v^\alpha(1, \mathbf{s}_t)$  and  $v^\alpha(0, \mathbf{s}_t)$  be the continuation value of entering the market given the state and exiting the market given the state respectively. In other words, the  $v^\alpha(\cdot, \mathbf{s}_t)$  are the non-random part of the value of choosing either of the two alternatives, given the current state. The  $\alpha$  notation indicates that we are looking for pairs of values  $v^\alpha(\cdot, \mathbf{s}_t) \forall \mathbf{s}_t \in \mathbf{S}$  and  $F^\alpha(\mathbf{s}_{t+1} | \cdot, \mathbf{s}_t) \forall \mathbf{s}_t \in \mathbf{S}$  such that these  $v^\alpha(\cdot, \mathbf{s}_t)$  imply the conditional distribution for the state transition process  $F^\alpha(\mathbf{s}_{t+1} | \cdot, \mathbf{s}_t)$  and the state transition process induces the values  $v^\alpha(\cdot, \mathbf{s}_t)$ . This gives us the following recursive expression for the value functions, which defines a system of equations:

$$v^\alpha(1, \mathbf{s}_t) = \Pi^\alpha(\mathbf{s}_t) + \delta \cdot \sum_{\mathbf{s}_{t+1} \in \mathbf{S}} \int \max \{v^\alpha(0, \mathbf{s}_{t+1}) + \epsilon'(0), v^\alpha(1, \mathbf{s}_{t+1}) + \epsilon'(1)\} dG(\epsilon') F^\alpha(\mathbf{s}_{t+1} | 1, \mathbf{s}_t) \quad \forall \mathbf{s}_t \in \mathbf{S} \quad (3)$$

$$v^\alpha(0, \mathbf{s}_t) = \Pi^\alpha(\mathbf{s}_t) + \delta \cdot \sum_{\mathbf{s}_{t+1} \in \mathbf{S}} \int \max \{v^\alpha(0, \mathbf{s}_{t+1}) + \epsilon'(0), v^\alpha(1, \mathbf{s}_{t+1}) + \epsilon'(1)\} dG(\epsilon') F^\alpha(\mathbf{s}_{t+1} | 0, \mathbf{s}_t) \quad \forall \mathbf{s}_t \in \mathbf{S} \quad (4)$$

We focus on symmetric Markov-perfect equilibria. Since we have four states  $S = \{(0, 0), (0, 1), (1, 0), (1, 1)\}$  we are solving a system of eight equations in eight unknowns, four of each  $v^\alpha(1, \mathbf{s}_t) \forall \mathbf{s}_t \in \mathbf{S}$  and  $v^\alpha(0, \mathbf{s}_t) \forall \mathbf{s}_t \in \mathbf{S}$ . When the player is in the market  $dG(\epsilon')$  is equal to one and  $\epsilon(0)$  is drawn uniformly from  $[0, 1]$ , which is the support of the scrap value distribution. The entry cost  $\epsilon(1)$  is always zero in this case. Likewise, if the player is outside of the market  $dG(\epsilon')$  is equal to  $\frac{1}{1+C}$  and  $\epsilon(1)$  is drawn uniformly from  $[C, 1 + C]$  whereas  $\epsilon(0)$  is zero in these states. Due to the possibility of multiple equilibria we solve this system of equations from many different starting values. In practice we always found only one solution to this system of equations for each of our parameter constellations of interest. While this is a strong indication that in our simple case there exists a unique equilibrium, we cannot entirely rule out that there are other equilibria that our numerical solver did not find. Note that once the  $v^\alpha(\cdot, \mathbf{s}_t)$  are obtained they imply a set of cutoff values for the scrap value and the random part of the entry cost, which imply the choice equilibrium choice probabilities.

## Collusive Equilibrium

Let  $\mathbf{p}(a = 1|s_t, \delta)$  be the vector of MPE choice probabilities. For  $\delta = 0.8$ , these are the choice probabilities, which are identified in *italics* in Table 2. These probabilities maximize the value function under the assumption that when both agents are in the market they play the stage Nash equilibrium and receive a payoff of  $2A - B$ . Likewise, let  $\mathbf{p}_c(a = 1|s_t, \delta)$  represent the probabilities that maximize the value function for the case that agents earn  $A$ , the collusive quantity choice outcome, whenever they are in the market.

The collusive quantity-stage outcome may be supported as an SPE if defection from the prescribed low quantity choice is punished. Strategies that support collusion have two phases: the collusion phase and the punishment phase. In the collusion phase both players select a low quantity in the first period and as long as both have always selected a low quantity in the past.<sup>49</sup> Under collusion they make their entry/exit decisions following the implied choice probabilities  $\mathbf{p}_c(a = 1|s_t, \delta)$ . We consider a punishment that is akin to grim-trigger: if one agent deviates from low production, then all entry/exit decisions are made according to  $\mathbf{p}(a = 1|s_t, \delta)$ ; and whenever both agents are in the market, the choice is high quantity (stage-game Nash). To express punishments formally, let  $m_t$  be given by:

$$m_t = \begin{cases} 0 & \text{if } q_{i,r} = q_{j,r} = 0 \text{ for all } r \leq t \text{ when } s_t = (1,1) \\ 1 & \text{otherwise} \end{cases}$$

In each period,  $m_t$  is therefore updated according to the latest quantity decisions. Due to the timing assumptions agents know  $m_t$  before they make their entry/exit decisions. If both agents have selected a low quantity (whenever both have been in the market) up to and including period  $t$ , then  $m_t$  takes on a value of 0. If any agent selected high production in any period up to and including  $t$ , then  $m_t$  takes a value of 1. Let  $\nu_{i,t}$  be the scrap value, or the random component of the entry cost, whichever corresponds to the state of the player. In our analysis we focus on grim-trigger strategies that specify an action for the quantity stage –in case both agents are in the market– and a decision rule for entry/exit choices. Hence, for each player  $i$  and time period  $t$  this class of strategies can be summarized by a pair  $(q_{it}, a_{it})$  such that:

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<sup>49</sup>Note that both players start in the market.

$$q_{it} = \begin{cases} 0 & \text{if } m_{t-1} = 0 \text{ or } t = 1 \\ 1 & \text{if } m_{t-1} = 1 \end{cases}$$

and

$$a_{it}(s_t) = \begin{cases} 1 & \text{if } \nu_{it} \leq p_c(s_t, \delta) \text{ and } m_t = 0 \\ 0 & \text{if } \nu_{it} > p_c(s_t, \delta) \text{ and } m_t = 0 \\ 1 & \text{if } \nu_{it} \leq p(s_t, \delta) \text{ and } m_t = 1 \\ 0 & \text{if } \nu_{it} > p(s_t, \delta) \text{ and } m_t = 1 \end{cases}$$

Let  $C(\delta)$  be the discounted value of collusion and let  $D(\delta)$  be the discounted value of playing according to the symmetric MPE. Now, consider deviations. To establish that a collusive strategy can be supported as an SPE we check whether there is a profitable deviation from such a strategy. According to the one-shot deviation principle it is enough to consider strategies that deviate in period  $t$  but otherwise (for every following period) conform to the collusive one. Whenever both agents are in the market in period  $t$ , an agent can deviate from the production decision, from the exit decision, or from both. By construction of  $p_c$  there are no incentives to deviate only in the exit decision. If there were, then  $p_c$  would not have been computed correctly. An agent could deviate in the production decision. In that case, they would receive a quantity stage payoff of  $2A$ . If one agent deviates in the quantity stage of period  $t$ , then  $m_t = 0$  and the exit decision in that period will be taken according to  $p$ . From period  $t+1$  onwards agents would be in the punishment phase for all future periods, but this involves playing according to the symmetric MPE, which is sub-game perfect. The payoff of a deviation is:  $Def(\delta) = 2A + \mathbb{E}[\nu | \nu > p(s_{it} = 1, s_{it} = 1)] \cdot (1 - p(s_{it} = 1, s_{it} = 1)) + \delta \times D(\delta)$ . The grim-trigger strategy is a sub-game perfect equilibrium for all  $\delta$  such that:  $Def(\delta) \leq C(\delta)$ .

In order to determine whether the trigger strategies constitute an SPE we first compute  $p_c$  for each treatment, which are reported in the second column of [Table 2](#). We then use these probabilities to check in each case if  $Def(0.8) < C(0.8)$ . Our treatment parameters are chosen so that trigger strategies *can* support the quantity-stage collusive outcome for  $A_S$  and  $A_M$  but not for  $A_L$ . Finally, we provide a measure of how much higher gains can be under the trigger strategies in each treatment. This measure captures how high the collusion incentives are and is summarized by the percentage increase of collusion over the MPE payoffs:  $GoC = 100 \cdot (C(0.8) - D(0.8))/D(0.8)$ . The figures are reported in the last row of [Table 2](#).

## Joint Monopoly Entry/Exit Probabilities

In the fully collusive equilibrium firms not only collude in the quantity decision, they also coordinate their entry and exit choices. To implement such a collusive strategy firms have to solve a private monitoring problem since the random parts of the entry cost and the scrap values are only privately observed by the players. We do not solve this private monitoring problem. However, to still be able to obtain a benchmark on how much higher the gains from collusion would be if firms also collude in the dynamic decision, we solve for the case in which firms know the entry cost and scrap values of the other firm. Under this assumption the problem can be solved as a simple single agent dynamic programming problem. For each of the possible four states  $\mathbf{s}_t \in \mathbf{S}$  the combined firm has four possible actions  $a_t \in \mathbf{A} = \{(0, 0), (0, 1), (1, 0), (1, 1)\}$ . We solve for the choice continuation values that summarize the non-random part of each of those four possible choices. In total there are sixteen equations:

$$v(a_t, \mathbf{s}_t) = \Pi(\mathbf{s}_t) + \delta \cdot \int \max_{a_t \in \mathbf{A}} \{v(a_t, \mathbf{s}_{t+1}) + \epsilon'(a_t)\} dG(\epsilon') F(\mathbf{s}_{t+1} | a_t, \mathbf{s}_t) \quad \forall \mathbf{s}_t \in \mathbf{S}, \forall a_t \in \mathbf{A} \quad (5)$$

Results are shown in [Table 8](#), which is similar to [Table 2](#) but includes the dynamic choice probabilities on the most collusive equilibrium. Interestingly, the probability to be in the market in each period is much lower compared to quantity-stage collusion for each of the four states. This result has a simple intuition. The combined market value is the same no matter whether there are two or only one firm in the market. Relative to the quantity-stage collusive equilibrium firms now coordinate on entry exit choices, which allows them to exploit the gains they can make from high scrap values and low entry cost. The prediction involves high turnover to exploit these gains.

Table 8: Cutoff-strategies for each treatment: MPE, CE and joint monopoly (MON)

Conditional probability	$A_S$			$A_M$			$A_L$		
	MPE (p)	CE (p <sub>c</sub> )	MON	MPE (p)	CE (p <sub>c</sub> )	MON	MPE (p)	CE (p <sub>c</sub> )	MON
$p(1, 0)$	0.458	0.519	0.504	0.688	0.823	0.652	0.880	0.925	0.683
$p(1, 1)$	0.360	0.512	0.492	0.596	0.784	0.602	0.781	0.870	0.610
$p(0, 0)$	0.260	0.368	0.354	0.498	0.663	0.505	0.681	0.757	0.554
$p(0, 1)$	0.161	0.362	0.340	0.408	0.624	0.467	0.583	0.702	0.457
Is collusion in quantities an SPE?	YES			YES			NO		
Gains from collusion in quantities	450.8%		481.1%	75.9%		93.22%	32.1%		51.98%

**Note:** This table presents the conditional choice probabilities for each of the four states as indicated in the left column. The choice probabilities are presented for each of the three market sizes, which we implement as treatments as indicated in the top row. Predictions are presented for the  $MPE(p)$  as well as the case where players collude in the marketstage,  $CE(p_c)$ . In the bottom the table indicates whether the collusive equilibrium we highlight can be supported as an SPE and how high the gains over MPE would be.

## Mapping Choice Probabilities to Value Functions

In this section we provide details on the estimation procedure. In a first stage we estimate the empirical dynamic choice probabilities  $P$  using simple frequency estimation, thus obtaining  $\hat{P}$ . This means we compute the fraction of time a player stays in the market or leaves the market respectively for each of the four states. Following the insight of Hotz and Miller (1993) the value function can be expressed in terms of these choice probabilities. Since all agents under the model assumption are planning with the equilibrium transitions that we estimate from the data we can directly solve for the value function in terms of these probabilities. We can write the value function as:

$$V = \sum_a P_a(\hat{P}) [u_a + e_a(\hat{P}) + \delta \cdot F_a(\hat{P}) \cdot V] \Leftrightarrow$$

$$V = [I - \delta \cdot \sum_a P_a(\hat{P}) \cdot F_a(\hat{P})]^{-1} [\sum_a P_a(\hat{P}) (u_a + e_a(\hat{P}))]$$

In our case with four states these objects take on a simple form:

$$V = [I - \delta \cdot [P_1(\hat{P}) \cdot F_1(\hat{P}) + P_0(\hat{P}) \cdot F_0(\hat{P})]]^{-1} [P_1(\hat{P}) \cdot (e_1(\hat{P}) + u_1) + P_0(\hat{P}) \cdot (e_0(\hat{P}) + u_0)] \quad (6)$$

with

$$u_1 = \begin{pmatrix} 0 \\ 0 \\ 2 \cdot A \\ 2 \cdot A - B \end{pmatrix} \quad u_0 = \begin{pmatrix} -C \\ -C \\ 2 \cdot A \\ 2 \cdot A - B \end{pmatrix} \quad e_1 = \begin{pmatrix} 0 \\ 0 \\ 1 - \frac{\hat{p}_3}{2} \\ 1 - \frac{\hat{p}_4}{2} \end{pmatrix} \quad e_0 = \begin{pmatrix} -\frac{\hat{p}_1}{2} \\ -\frac{\hat{p}_2}{2} \\ 0 \\ 0 \end{pmatrix}$$

$$P_1 = \begin{bmatrix} \hat{p}_1 & 0 & 0 & 0 \\ 0 & \hat{p}_2 & 0 & 0 \\ 0 & 0 & \hat{p}_3 & 0 \\ 0 & 0 & 0 & \hat{p}_4 \end{bmatrix} \quad P_0 = \begin{bmatrix} 1 - \hat{p}_1 & 0 & 0 & 0 \\ 0 & 1 - \hat{p}_2 & 0 & 0 \\ 0 & 0 & 1 - \hat{p}_3 & 0 \\ 0 & 0 & 0 & 1 - \hat{p}_4 \end{bmatrix}$$

$$F_1 = \begin{bmatrix} \hat{p}_1 & 1 - \hat{p}_1 & 0 & 0 \\ \hat{p}_3 & 1 - \hat{p}_3 & 0 & 0 \\ \hat{p}_2 & 1 - \hat{p}_2 & 0 & 0 \\ \hat{p}_4 & 1 - \hat{p}_4 & 0 & 0 \end{bmatrix} \quad F_0 = \begin{bmatrix} 0 & 0 & \hat{p}_1 & 1 - \hat{p}_1 \\ 0 & 0 & \hat{p}_3 & 1 - \hat{p}_3 \\ 0 & 0 & \hat{p}_2 & 1 - \hat{p}_2 \\ 0 & 0 & \hat{p}_4 & 1 - \hat{p}_4 \end{bmatrix}$$

In the previous expressions, we use the following shortened notation:  $p_1 = p(a = 1|s = (0, 0))$ ,  $p_2 = p(a = 1|s = (0, 1))$ ,  $p_3 = p(a = 1|s = (1, 0))$ ,  $p_4 = p(a = 1|s = (1, 1))$ . Note that Equation 6 expresses the value function only in terms of parameters and objects that are composed of observables. The following section shows briefly how the expected values  $e_1(\hat{P})$  and  $e_0(\hat{P})$  are obtained from choice probabilities as indicated above. For a given parameter guess and choice probabilities we therefore form a guess  $\hat{V}$ . Once we know  $\hat{V}$ , we can easily compute  $\hat{v}(1, s_t) \forall s_t \in \mathbf{S}$  and  $\hat{v}(0, s_t) \forall s_t \in \mathbf{S}$  from this.

## Choice Probabilities and Expectations for the Uniform

Let  $\mathbf{x}_{out}$  denote the states in which the player is out and  $\mathbf{x}_{in}$  be the states in which he is in. For the entry-case under  $\psi \sim U[0, 1]$  and  $0 \leq (v(1|\mathbf{x}_{out}) - v(0|\mathbf{x}_{out})) \leq 1$  we have:

$$E[\psi | \psi < v(1|\mathbf{x}_{out}) - v(0|\mathbf{x}_{out})] = \int_0^{v(1|\mathbf{x}_{out}) - v(0|\mathbf{x}_{out})} \psi \frac{1}{v(1|\mathbf{x}_{out}) - v(0|\mathbf{x}_{out})} d\psi =$$

$$\frac{\psi^2}{2} \frac{1}{v(1|\mathbf{x}_{out}) - v(0|\mathbf{x}_{out})} \Big|_0^{v(1|\mathbf{x}_{out}) - v(0|\mathbf{x}_{out})} = \frac{(v(1|\mathbf{x}_{out}) - v(0|\mathbf{x}_{out}))}{2} = \frac{P(in)}{2}$$

For the exit case under  $\phi \sim U[0, 1]$  and  $0 \leq (v(1|\mathbf{x}_{out}) - v(0|\mathbf{x}_{out})) \leq 1$  we have:

$$E[\phi | v(1|\mathbf{x}_{in}) - v(0|\mathbf{x}_{in}) < \phi] = \int_{v(1|\mathbf{x}_{in}) - v(0|\mathbf{x}_{in})}^1 \phi \frac{1}{1 - (v(1|\mathbf{x}_{in}) - v(0|\mathbf{x}_{in}))} d\phi$$

$$= \frac{1 + (v(1|\mathbf{x}_{in}) - v(0|\mathbf{x}_{in}))}{2} = 1 - \frac{P(in)}{2}$$

## Monte Carlo

### Data Generating Process

We generate data either under the assumption of the symmetric MPE or the CE play for our parametrizations. We assume that there are 300 pairs of firms and each pair of firms is considered to be isolated from the rest. The interaction between each pair of firms ends after each period with probability 0.2, which corresponds to the discount implemented in the laboratory. For the Monte Carlo study we will estimate parameters using 100 such data sets and subsample each data set 30 times to obtain standard errors.

Table 9: Monte Carlo results

Parameter	$A_S$			$A_M$			$A_L$	
	Estimates		True value	Estimates		True value	Estimates	True value
	MPE	CE		MPE	CE			
$A$	0.052 (0.012)	0.044 (0.045)	0.05	0.249 (0.03)	0.246 (0.049)	0.25	0.390 (0.041)	0.4
$B$	0.620 (0.130)	0.032 (0.173)	0.6	0.611 (0.132)	0.24 (0.144)	0.6	0.575 (0.111)	0.6
$C$	0.142 (0.029)	0.148 (0.04)	0.15	0.146 (0.032)	0.148 (0.021)	0.15	0.153 (0.027)	0.15

**Note:** The table shows the results of the Monte Carlo estimation. For each of the three values of  $A$  it shows the estimates if the econometrician assumes the correct data generating process (MPE) as well as the estimates if the econometrician incorrectly assumes the MPE and the data is in fact coming from decisions on the equilibrium path of the highlighted collusive equilibrium (CE) for  $A_M$  and  $A_S$ . In the case of  $A_L$ , the CE is not an SPE. Estimates are averages over 100 datasets. Each dataset assumes 300 markets of an average length of five periods (market terminates randomly with probability 0.2). Standard errors are shown in parentheses below the estimates and are obtained by subsampling each data-set 30 times.

## Monte Carlo Estimates

For each value of  $A$ , Table 9 presents the Monte Carlo estimates. In the “MPE” column we present estimates when firms’ play is generated according to the symmetric MPE, while in the “CE” column we display estimates when firms are assumed to follow the Collusive Equilibrium (and the econometrician wrongfully assumes MPE play). By comparing estimates in the “MPE” column with the True Value column treatment by treatment we verify that the parameters can be recovered with tight standard errors from a data set of modest size.<sup>50</sup>

Comparing the CE estimates to the true value we notice that the bias from an incorrect assumption on the equilibrium shows up in  $B$ . The parameter that captures the competitive effect would be biased downwards. Intuitively, the estimator in recovering  $B$  compares the choices of firm  $i$  when firm  $-i$  is in the market to those when firm  $-i$  is not in the market. For

<sup>50</sup>We also ran versions of the Monte Carlo in which players’ cost depends on individual specific cost shifters that are observable to the econometrician. Such cost shifters would help to considerably improve the standard error of the interaction term  $B$  and improved identification at the limits of the parameter space. Under the current specification, the only observable variable that shifts player  $i$ ’s action is the action of player  $-i$ . Because of this minimal structure of the model, parameter estimates become noisy for  $B$  values very close to zero, where the influence of the other player vanishes. However, in the experiment, other observable cost shifters (i.e. some variable  $x$  not determined endogenously) would have increased the number of necessary treatments and the complexity considerably, which is why we decided against such a setup.

example, consider market  $A_S$  and assume firm  $i$  is currently in the market. Because the CE data is generated according to the second column of [Table 2](#), firm  $i$  will be in the market next period with probability 0.519 or 0.512, depending on whether firm  $-i$  is in the market or not. This small difference in probabilities (a small effect of competition) will be rationalized with an estimate for  $B$  that is smaller than the true value. In other words, a lower estimate for  $B$  is consistent with the presence of collusion.

### Monte Carlo Counterfactuals

For each baseline we perform an exercise in which there is full collusion in the Monte Carlo generated data, but the econometrician wrongly assumes that there is no collusion. Then the econometrician uses the estimates to predict behavior for other market sizes. To document the maximum possible error in counterfactual predictions we assume that in each counterfactual there is actually no collusion in the data.

The bias (as in Section 5.4 of the paper) is computed as the percentage deviation in the value of the firm from the true value of the firm under the correct data generating process for each state. The results are shown in [Table 21](#). We then collapse these measures into a single measure assigning equal weight to each state, what we refer to in Section 5.4 as MAPE (V). No bias would result in a MAPE (V) of zero. These Monte Carlo results emphasize that proper collusion if not accounted for by the econometrician would severely bias counterfactual computations. [Table 21](#) shows that the overestimate ranges from  $\approx 36\%$  to  $\approx 110\%$ .

	$A_L$	$A_M$	$A_S$
<b>Baseline/Counterfactual</b>	MAPE(V)	MAPE(V)	MAPE(V)
$A_L$	-	35.4	56.5
$A_M$	60.9	-	107.6
$A_S$	107.3	113.5	-

Table 10: Maximal counterfactual error from collusion (in %)

This table (based on Monte Carlo results and NOT data) shows the maximal resulting bias if the econometrician wrongly assumes that firms do not collude in the baseline and predicts the outcomes in a market (of the same market size) under the correct assumption that firms in the counterfactual do not collude.



## Appendix B

In this appendix we study entry/exit choices in more detail. We first provide detailed hypotheses on comparative statics, which are afterwards tested.

### Comparative Static Hypotheses

We now explicitly formulate MPE comparative statics in terms of entry and exit thresholds using Table 2 as a reference. We can then contrast these predictions under MPE play with what we actually observe in the data.

**Comparative Statics 1 (CS1): Exit vs. Entry thresholds (within treatment).** *Exit thresholds are predicted to be higher than entry thresholds.*

In addition, there are predictions on how entry and exit thresholds should vary as a response to the state of the other player (i.e. compare thresholds for  $s(\cdot, 1)$  to  $s(\cdot, 0)$ ). When the other is in the market there is competition, and quantity-stage payoffs correspond to the static Nash equilibrium; these payoffs are lower than the (static monopoly) payoffs the agent gets when the other is out of the market. In the equilibrium this is captured with a difference between the two exit thresholds and a difference between the two entry thresholds. We refer to these predictions as the “effect of competition” on thresholds.

**Comparative Statics 2 (CS2): Effect of competition in thresholds (within treatment).** *Fix the agent’s own current state. Thresholds are higher when the other player is currently out than when the other player is currently in the market.*

The MPE also provides comparative statics across treatments. As the value of  $A$  increases, the relative attractiveness of the market also increases and all corresponding thresholds are higher: agents demand higher exit payments to leave the market and are willing to pay higher entry fees to go in. This prediction is summarized below:

**Comparative Statics 3 (CS3): Between treatments:** *All thresholds increase monotonically with  $A$ .*

The Collusive Equilibrium also provides hypotheses on comparative statics. For example, exit and entry thresholds should respond to market behavior according to the collusive strategy: the market is relatively less valuable after the other agent deviates from collusive behavior. As a consequence, agents would be willing to leave for lower scrap values and would be willing to pay less in order to re-enter the market.<sup>51</sup> We now state this as a hypothesis.

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<sup>51</sup>As mentioned earlier, the characterized collusive equilibrium is one of possibly many equilibria that support collusion in the quantity

**Collusion Hypothesis 1 (CH1): Effect of Defection on Thresholds.** *According to the Collusive Equilibrium, entry and exit thresholds are lower in all periods after defection in the quantity stage.*

Finally, we can also use [Table 2](#) and compare thresholds between treatments that allow and that do not allow for a quantity choice.

**Collusion Hypothesis 2 (CH2): Standard vs. No Quantity Choice treatments.** *Fix the value of  $A$  and compare Standard treatments to treatments with No Quantity Choice. There is evidence consistent with the presence of collusion if: 1) the effect of competition is lower in the Standard treatments; and 2) if thresholds for all states are higher in the Standard treatments.*

## States

There are large differences across treatments in terms of states' frequencies, which are presented in [Table 11](#). Considering the unit of observation as a pair of subjects in each period of each supergame there are three possible states the pair can be at: both are out of the market, one out and the other in or both are in the market. The table shows the proportion of periods in which a pair was in either of these three states by treatment. Period 1 of every match is omitted as by definition all subjects start out, so that the table only shows the results of endogenous decisions.

There are clear patterns in the table. First, being out of the market is more likely when  $A$  is lower. The state when both are out reaches the highest share for  $A_S$  and its occurrence diminishes when  $A$  is higher. In fact, in only very few occasions do we observe pairs of subjects in this state for  $A_L$ . The opposite situation is observed for the state when both are in, which reaches the highest share for  $A_L$ . The lower likelihood of being out in the large market size treatment will have consequences on the accurateness of the average entry threshold estimate. This will be reflected as relatively larger confidence intervals as can be seen in [Figure 2](#).

The second pattern is that the likelihood of being out is higher when there is No Quantity Choice as long as  $A$  is not at the highest level. Consider, for instance,  $A_S$ . The proportion of times that both agents are out of the market is clearly larger when there is No Quantity Choice. This is consistent with the fact that quantity choices present the alternative to obtain higher payoffs and thus have the potential of making staying in the market more attractive. The effect

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stage. However, any punishment phase that achieves collusion in the quantity stage is expected to involve lower thresholds. If collusion in the quantity stage cannot be supported, then being in the market is less valuable, which is reflected by lower thresholds.

Treatment	State		
	Both Out	One Out-One In	Both In
$A_S$ , No Quantity Choice	34.8	51.2	14.0
$A_S$ , Standard	22.9	49.7	27.4
$A_M$ , No Quantity Choice	9.5	48.1	42.5
$A_M$ , Standard	5.7	41.1	53.2
$A_L$ , No Quantity Choice	2.8	32.5	64.7
$A_L$ , Standard	2.6	31.5	65.9

Table 11: States by treatment after period 1 (in percentages)

is smaller for  $A_M$  and almost indistinguishable for  $A_L$ , when there is a negligible number of cases in either treatment where both agents are out of the market.

### Within Treatment Hypotheses on Thresholds

To test for the main within treatment hypotheses (CS1, CS2), we will use panel data analysis. We conduct one regression per treatment, which are reported in [Table 12](#). The left-hand-side variable in all cases is the threshold selected by each subject. If in the corresponding period the subject is deciding to exit (enter) the market, the threshold variable captures their report for the exit (entry) threshold. On the right-hand side there are four variables. We exclude the state when the subject is out and the other is in the market ( $s = (0, 1)$ ), which in theory corresponds to the case where the subject is least likely to enter the market next. Naturally, the excluded state will be captured by the constant, and we add a dummy for each of the three other possible states. Depending on the state, the corresponding dummy will report the increment to the baseline threshold defined by the constant.

CS1 predicts that exit thresholds are higher than entry thresholds. This translates into four comparisons by treatment, and in all 24 cases the differences are significant at the 1% level in the direction predicted by the theory. In other words, there is strong support for this hypothesis, which indicates that subjects do respond to one of the most basic incentives of the

game.

There is also evidence in favor of CS2. In this case, the hypothesis implies two comparisons by treatment: fixing  $s_i$  and testing whether there is a difference depending on the state of the other. For the case when the subject is out of the market, the outcome for the comparison is readily available in the estimates for coefficient ( $s = (0, 0)$ ). In all cases the estimate is positive: subjects are willing to pay more to enter the market if the other is out. However, the coefficient is significant at the 5% level for  $A_M$  treatments and at the 10% level in two other cases. Moreover, while the theory predicts a 10-point difference (see Table 2), the estimate is quantitatively smaller in all cases. The effect of competition, however, is more evident when the subject is in the market. In this case, the difference between the coefficients ( $s = (1, 1)$  and  $s = (1, 0)$ ) is always as predicted by the theory and significant in all treatments. In a few words, all comparisons are in line with the prediction and all but two are significant at least at the 10% level.

Table 12: Panel regressions: Within treatment hypotheses

Variable	$A_S$		$A_M$		$A_L$	
	Standard	No Quantity Choice	Standard	No Quantity Choice	Standard	No Quantity Choice
Intercept	20.377*** (2.412)	19.273*** (2.494)	36.365*** (3.001)	33.879*** (3.666)	45.488*** (5.503)	37.391*** (3.471)
$s = (0, 0)$	2.310* (1.375)	1.150 (2.431)	5.828*** (1.077)	5.387*** (1.306)	2.302 (5.575)	1.658* (0.915)
$s = (1, 1)$	47.587*** (2.709)	34.768*** (5.136)	46.913*** (6.465)	42.930*** (6.102)	41.026*** (8.394)	49.589*** (2.272)
$s = (1, 0)$	54.119*** (3.306)	50.047*** (6.494)	51.202*** (5.700)	49.650*** (5.084)	46.221*** (6.678)	53.658*** (1.032)

Note: This table provides reduced form analysis of the within treatment comparative statics. The dependent variable is the selected threshold (entry or exit) that corresponds to the state. The independent variables are dummies for each state where the state ( $s = (0, 1)$ ) is the excluded category. Standard Errors reported between parentheses, Significance levels: 1%(\*\*\*), 5%(\*\*), 10%(\*) Standard Errors are clustered at the session level

The analysis so far has focused on centrality measures, which are key for computing structural estimates. To provide a broader perspective of our data, Figure 4 displays the cumulative distributions of thresholds by state for all treatments. Some patterns are present across treatments. First, the distributions are largely ordered as predicted by the symmetric MPE. Entry thresholds display lower values than exit thresholds, and within each case subjects largely

select higher values when the other is out. Second, most distributions suggest that values are centered around the mean. For example, in the case of the  $A_S$ -Standard treatment, entry thresholds display a significant mass between the relatively lower values (20 and 40), while most of the mass in the case of exit thresholds is between 70 and 80.

## Between Treatment Hypotheses on Thresholds

We now test statements that involve comparisons that depend on the value of  $A$  or on whether there is a quantity stage or not. With this aim we conduct two panel regressions, one for exit and one for entry thresholds. More specifically, the “Entry Threshold” regression only considers periods when subjects had to select an entry threshold. The selected entry threshold constitutes the left-hand side variable. On the right-hand side there are two sets of dummies. The excluded group corresponds to the  $A_S$ -Standard case. The first set of dummies will capture the differential effect corresponding to the other five treatments. The second set of dummies interacts the treatment dummy with the state of the other player. That is, for each treatment there is a dummy that takes value 1 if the other is out of the market. The second regression uses the same controls, but considers exit thresholds on the left-hand side instead. The results are reported in [Table 13](#).

CS3 states that thresholds increase with market size. There are 24 comparative statics: for each of the four states there are three comparisons, and such comparisons can be made for treatments with and without a quantity stage. Not all comparative statics are statistically significant, but all differences are in the direction predicted by the hypothesis. In all treatments the difference in entry and exit thresholds is significant at the 1% level when comparing the  $A_S$  treatment to either of the other market sizes. When comparing the  $A_M$  to  $A_L$ , the difference between thresholds is statistically significant at the 5% level only for exit thresholds when there is No Quantity Choice. In other cases differences are not statistically significant. Overall this means that in 18 out of 24 comparisons differences are statistically significant.

Section 3 also presented hypotheses that would be consistent with the presence of collusion. Part 1 of CH2 claims that there is evidence consistent with the presence of collusion if the effect of competition is lower when there is a quantity choice. There would be evidence supporting the claim if fixing the market size, the interaction dummy is significantly higher when there is a quantity stage. Again, in all six comparisons the differences are in the direction predicted by the hypothesis. For entry thresholds the differences are significant at the 5% and

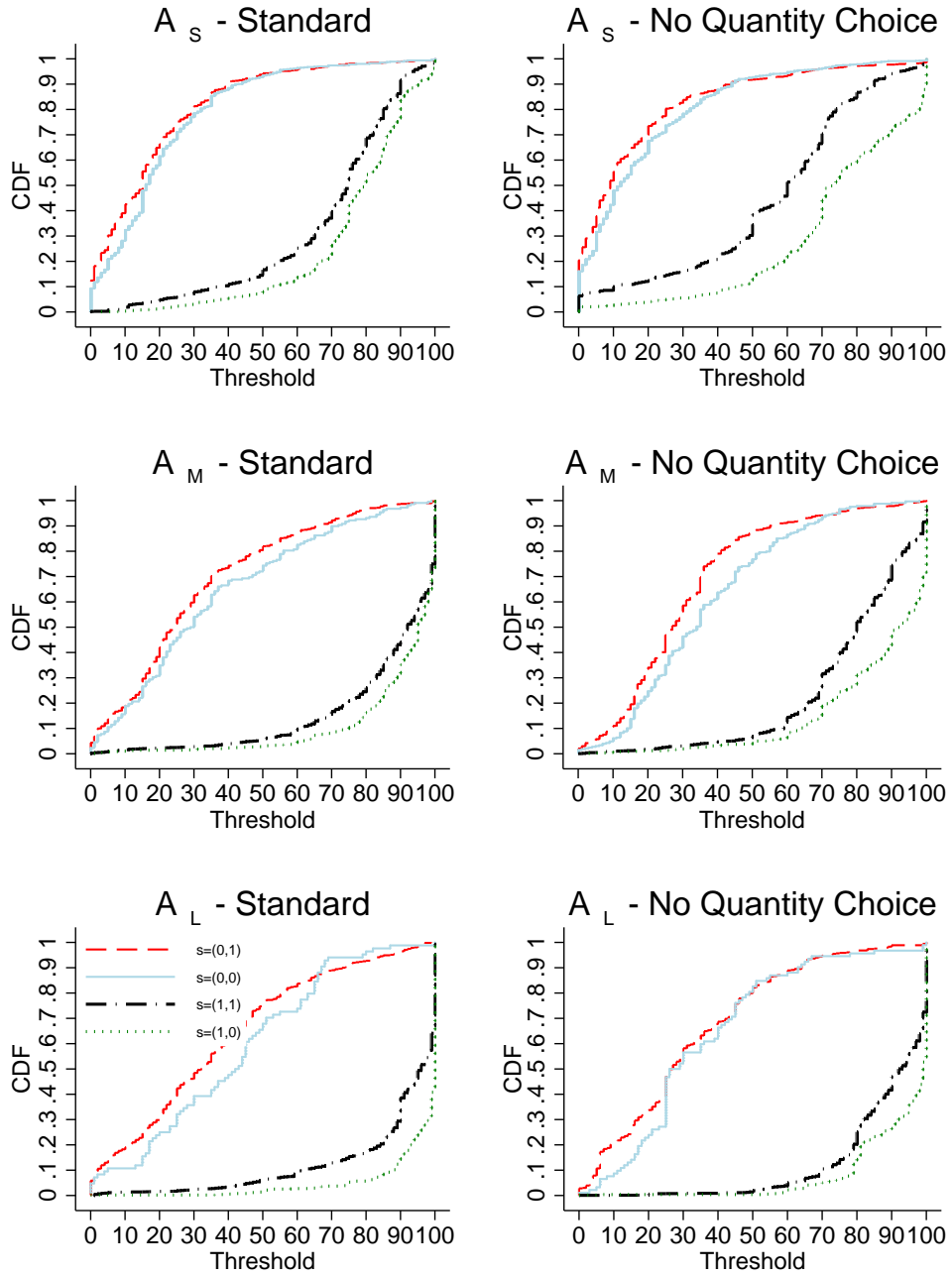


Figure 4: Cumulative distributions of thresholds across treatments

10% level for  $A_M$  and  $A_L$ , respectively. For exit thresholds, the differences are significant at the 1% level only for  $A_S$ .

Fixing the market size collusion is consistent with higher thresholds when there is a quantity choice, which constitutes part 2 of CH2. This hypothesis involves 12 comparisons using the estimates presented in [Table 13](#). For example, consider the entry threshold regression and  $A_M$ . The hypothesis claims two comparisons, depending on whether the other is in or not: i) the coefficient for  $A_M$ -S is higher than for  $A_M$ -NQ, and ii) adding the coefficients for  $A_M$ -S and the interaction  $A_M$ -S  $\times$  Other Out is lower than the addition of the same coefficients but when there is no quantity choice. The direction of the differences is in line with the prediction in all cases, but differences are not significant with the exception of the exit threshold for  $A_S$  size when the other is in the market.

Table 13: Panel regressions: Between treatment hypotheses

Variable	Entry Threshold	Exit Threshold
Intercept	22.001*** (1.955)	67.131*** (1.951)
$A_S$ -NQ	-3.110 (2.988)	-14.547*** (3.337)
$A_M$ -S	10.046*** (3.566)	14.652*** (4.055)
$A_M$ -NQ	10.858*** (2.681)	9.000*** (3.177)
$A_L$ -S	13.498*** (2.578)	18.087*** (4.258)
$A_L$ -NQ	12.320*** (4.207)	19.482*** (2.585)
$A_S$ -S $\times$ Other Out	1.406* (0.830)	7.490*** (1.380)
$A_S$ -NQ $\times$ Other Out	1.968 (2.595)	14.398*** (1.310)
$A_M$ -S $\times$ Other Out	2.204*** (0.450)	4.479*** (0.635)
$A_M$ -NQ $\times$ Other Out	3.945*** (0.348)	6.476*** (1.725)
$A_L$ -S $\times$ Other Out	1.139*** (0.229)	3.521*** (1.219)
$A_L$ -NQ $\times$ Other Out	4.297** (1.836)	3.802*** (1.390)

**Note:** Standard Errors reported between parentheses, Significance levels: 1%\*\*\*), 5%(\*\*), 10%(\*), Standard Errors are clustered at the session level. S: indicates Standard treatment; NQ indicates No Quantity Choice treatment.



## Effect of Quantity-Stage Choices on Thresholds

CH1 claims that entry and exit thresholds are lower after defection. We present the results of a random-effects probit regression where the left-hand side is the exit (or entry) threshold and on the right-hand side there is a set of dummy variables that capture the outcome for the last time subjects were in the market.<sup>52</sup> Table 14 displays the results of these regressions for each treatment.

Several patterns emerge. First, consider exit thresholds. In  $A_S$  and  $A_M$  treatments subjects are more responsive to last period's outcome. In these cases, subjects are significantly more likely to select a higher exit threshold, while if the other defected in the previous market interaction they are more likely to select a lower threshold. This last effect is also present for  $A_L$ . When, instead, we look at entry thresholds, the pattern is less clear. It appears that in most cases subjects are less responsive to recent market behavior when they are out of the market.

Outcome Last Quantity Stage	$A_S$				$A_M$				$A_L$			
	Exit Threshold		Entry Threshold		Exit Threshold		Entry Threshold		Exit Threshold		Entry Threshold	
	Coeff.	Std. Err.	Coeff.	Std. Err.	Coeff.	Std. Err.	Coeff.	Std. Err.	Coeff.	Std. Err.	Coeff.	Std. Err.
(Collude, Collude)	5.551***	0.956	0.997	0.947	5.688***	0.622	4.478**	1.916	0.108	0.618	.704	3.479
(Collude, Defect)	-6.867***	1.172	-1.848*	1.01	-1.965***	0.772	-1.013	1.657	-1.940***	0.719	4.361	2.761
(Defect, Collude)	-1.319	-1.17	-0.306	0.931	-0.377	0.773	0.538	1.484	-0.876	.126	4.885	3.073
Constant	69.484***	1.868	37.84***	2.639	81.81***	2.246	47.08***	2.982	85.88***	.124	49.7***	3.396

Notes: The dependent variable is the threshold selected by subject  $i$ . The right-hand side variables include possible outcomes from last quantity stage, where the first action corresponds to the choice of subject  $i$ . Significant at: \*\*\* 1%, \*\*5%, \*10%

Table 14: Effect of past market choices on thresholds

## Choices As the Session Evolves

In principle it is possible that choices in the aggregate change as the session evolves. Figures 5 and 6 display average exit and entry thresholds for each supergame for each possible state a subject may be at, for Standard and No Quantity Choice treatments, respectively. Visual inspection suggests that in most cases a trend is not evident, which we indeed confirm with statistical analysis.<sup>53</sup> If we add a dummy for each supergame to the regressions of Tables

<sup>52</sup>In cases where subjects are deciding on an exit threshold the last period for which there is an outcome is the current period. The reference is to the last period in which there was a market choice in the case of entry thresholds.

<sup>53</sup>The case of entry thresholds for  $A_L$  when the other is not in the market does display volatility, but this is due to the relatively low number of observations (see Table 11).

12 and 13 the message is similar. In a few cases there is a significant effect of a particular supergame; when such effect is present it happens in the earlier supergames of the session and is quantitatively very small.

It is also possible that subjects change the thresholds within a supergame. This may be because they are following a strategy that conditions the threshold on past play (i.e. as in the CE) or because they follow a strategy that conditions on a particular period. We know that some subjects may be conditioning their thresholds on past play given that some aggregate choices are consistent with CH1. In order to test if there is a strong pattern in aggregate thresholds depending on the period, we include the regressions in Table 12: a) a set of period dummies and b) interactions of each period dummy with the dummy that takes value 1 if the other is not in the market. Results show that there is no clear pattern that indicates a period effect at the aggregate level.<sup>54</sup>

## Summary

We now summarize the main findings in this appendix:

- There is broad support in the data for the comparative statics predicted by the symmetric MPE. Out of 60 comparisons implied by CS1, CS2 and CS3 all differences are in the predicted direction and 50 (52) are significant at least at the 5% (10%) level.
- There is evidence that is consistent with market collusion having an effect on threshold choices. The effect of market collusion on threshold choices appears to be higher for  $A_S$  and  $A_M$ , and for exit thresholds.
- The evidence does not indicate substantial changes in aggregate behavior as the session evolves.

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<sup>54</sup>Given the large set of controls we do not report these regressions, but they are available upon request.

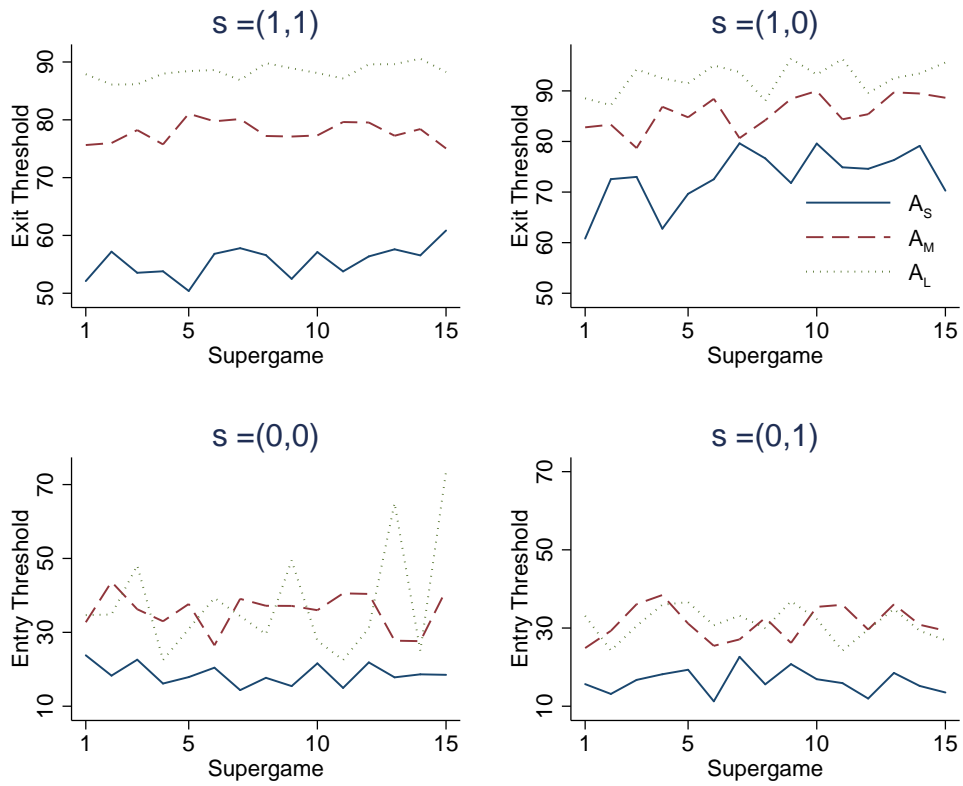


Figure 5: Evolution of thresholds: No Quantity Choice treatments

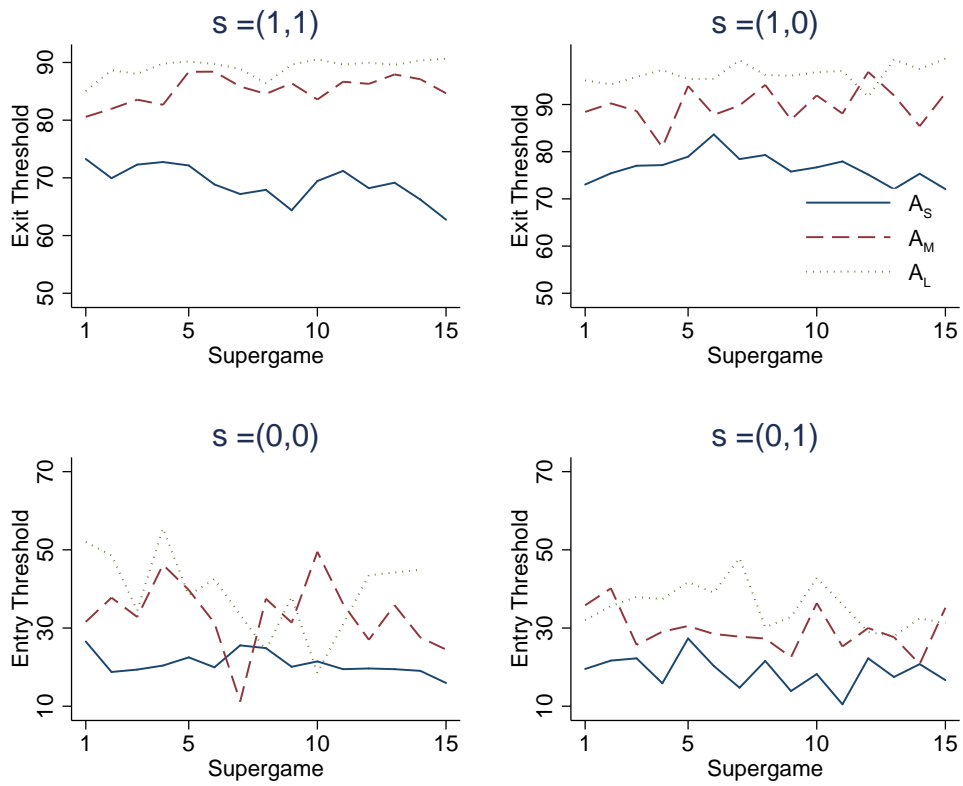


Figure 6: Evolution of thresholds: Standard treatments

## Appendix C

This appendix provides additional analysis on the quantity-stage choice. Figure 7 displays the cooperation rate taking all periods of a supergame into consideration and basically reproduces the same broad patterns presented in Figure 8, which only takes into account cooperation in the first period of each supergame. Cooperation rates after period 1 will be endogenously affected by behavior within the supergame. In this section we use two approaches to better understand the determinants of quantity-stage choices. First, we take a non-structural approach and use panel regression analysis to study how cooperation in period  $t$  is affected by behavior in previous periods and supergames. Second, we use a structural method to study which strategies better capture subjects' choices. Finally, we study further the connections between quantity-stage and entry/exit-stage choices.

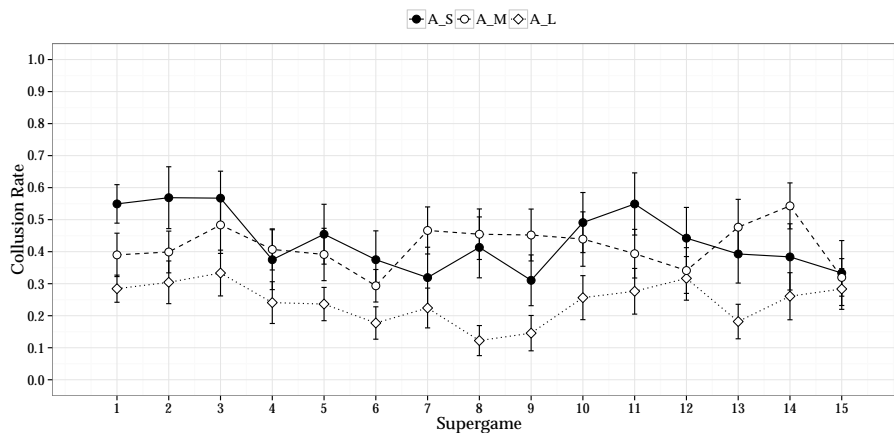


Figure 7: Cooperation rates (all)

### Cooperative Behavior: A Non-Structural Approach

To further study decisions in the quantity stage we run random effects probit regressions where the market action is the variable on the left-hand side (1: cooperation) and the right-hand side includes a series of usual controls. We control for the subjects' last choice (Own past action) and their partner's past action (Other's past action) last time they were in the market, and we include period 1 decisions to control for dynamic unobserved effects. There are also three dummies to capture the state in the last period, where the state in which both subjects are

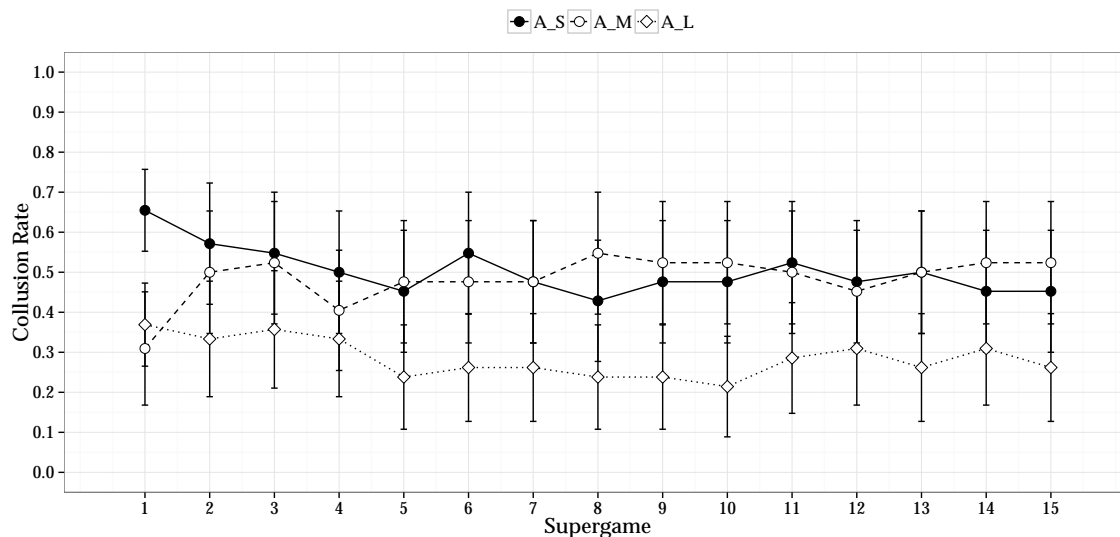


Figure 8: Cooperation rates (first period)

out is omitted. Match dummies and period dummies are also included, but for space reasons omitted in [Table 15](#).

Several patterns are consistent across treatments. First of all, the likelihood of cooperation is higher when the subject or the other colluded last time they were in the market. In fact, the probability of cooperating is higher when the other colluded previously. Second, the dummy for the likelihood of cooperation if the state last period was  $(1, 0)$  is the most negative in all treatments. This indicates that subjects are least likely to cooperate coming from a situation when they were in the market, but the other was out. This also suggests that some subjects may choose to be less cooperative in the market in order to incentivize the other to leave the market.

## Recovering Strategies Using SFEM

Cooperation rates provide one measure of collusion, but there are techniques –the Strategy Frequency Estimation Method (SFEM) of Dal Bó and Fréchette (2011)– that recover which strategies best rationalize the data. This would tell us to what extent choices in treatments where collusion can be supported as an SPE are consistent with the CE.<sup>55</sup>

<sup>55</sup>In principle, another alternative consists of regressing choices on past play. However, such an exercise can be misleading. For example, if only a small proportion of subjects are consistently conditioning their choices on some aspect of the history, the associated coefficient can

Variable	$A_S$		$A_M$		$A_L$	
	Coeff.	Std. Err.	Coeff.	Std. Err.	Coeff.	Std. Err.
Own past action	0.369***	0.124	.784***	0.095	.836***	0.105
Other's past action	0.857***	0.121	.966***	0.103	1.259***	0.119
Own action in period 1	2.191***	0.150	2.039***	0.124	1.336***	.126
Other's action in period 1	0.659***	0.120	0.809***	0.107	0.738***	.124
$s_{t-1} = (0, 1)$	-0.262	0.191	-0.943***	0.186	-0.215	.198
$s_{t-1} = (1, 0)$	-1.256***	0.223	-1.264***	0.186	-0.929***	.246
$s_{t-1} = (1, 1)$	-0.913***	0.119	-1.049***	0.105	-0.710***	.116

Note: Significant at: \*\*\* 1%, \*\*5%, \*10%

Table 15: Random effects probit results

In order to outline how the SFEM works, consider an infinitely repeated prisoners' dilemma. The game involves just a static decision, where in every period the agent faces a binary choice (cooperate or defect), as if both subjects were in the market. In that simpler environment there is a large set of possible strategies  $\sigma$  an agent can follow. Strategies may depend on past behavior, and it is possible to compute for each  $\sigma \in \Sigma$  what choices the subject would have made had she been exactly following strategy  $\sigma$ . On the other hand we have the subject's actual choices. The unit of observation is a *history*: the set of choices a subject made within a supergame. The SFEM procedure works as a signal detection method and estimates via maximum likelihood how close the actual choices are from the prescriptions of each strategy. The output is the frequency for each strategy in the population sample.

To describe the method in further detail, assume that the experimental data has been generated for an infinitely repeated prisoners' dilemma and define  $ch_{i,cr}$  as the choice of subject  $i$  in period  $p$  of supergame  $g$ ,  $ch_{i,gp} \in \{Cooperate, Defect\}$ . Consider a set of  $K$  strategies that specify what to do in round 1 and in later rounds depending on past history. Thus, for each history  $h$ , the decision prescribed by strategy  $k$  for subject  $i$  in period  $p$  of supergame  $g$  can be computed:  $h_{i,gp}(h^k)$ . A choice is a perfect fit for a history if  $ch_{i,gp} = h_{i,gp}(h^k)$  for all rounds of the history. The procedure allows for mistakes and models the probability that the choice

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turn out to be significant. We could mistakenly conclude that past play does have an effect in the population, while it is actually driven by a small share. The technique we use, on the other hand, allows us to estimate the proportion of choices that can be better rationalized as conditioning on past play. We would, thus, observe if such proportion is a small share or not. More generally, using standard regression analysis to evaluate whether behavior is Markovian or not can be very misleading; see Vespa (2019) for more details.

corresponds to a strategy  $k$  as:

$$Pr(ch_{igp} = h_{igp}(h^k)) = \frac{1}{1 + \exp\left(\frac{-1}{\gamma}\right)} = \beta. \quad (7)$$

In (7)  $\gamma > 0$  is a parameter to be estimated. As  $\gamma \rightarrow 0$ , then  $Pr(ch_{igp} = h_{igp}(h^k)) \rightarrow 1$  and the fit is perfect. Define  $y_{igp}$  as a dummy variable that takes value one if the subject's choice matches the decision prescribed by the strategy,  $y_{igp} = 1 \{ch_{igp} = h_{igp}(h^k)\}$ . If (7) specifies the probability that a choice in a specific round corresponds to strategy  $k$ , then the likelihood of observing strategy  $k$  for subject  $i$  is given by:

$$p_i(s^k) = \prod_g \prod_p \left( \frac{1}{1 + \exp\left(\frac{-1}{\gamma}\right)} \right)^{y_{igp}} \left( \frac{1}{1 + \exp\left(\frac{1}{\gamma}\right)} \right)^{1-y_{igp}} \quad (8)$$

Aggregating over subjects:  $\sum_i \ln(\sum_k \phi_k p_i(s^k))$ , where  $\phi_k$  represents the parameter of interest, the proportion of the data which is attributed to strategy  $s^k$ . The procedure recovers an estimate for  $\gamma$  and the corresponding value of  $\beta$  can be calculated using (7). The estimate of  $\beta$  can be used to interpret how noisy the estimation is. For example, with only two actions a random draw would be consistent with  $\beta = 0.5$ .

Our environment is more complex than an infinitely repeated prisoners' dilemma; it involves a dynamic (continuous) and a static (discrete) choice. While the SFEM procedure is designed to study discrete choices, we can still use it to learn about the strategies that rationalize our subjects' quantity choices. A necessary condition for CE is that subjects follow a grim-trigger strategy whenever both are in the market. Likewise, a necessary condition for the symmetric MPE is that both subjects always defect from cooperation in the static choice. We use the SFEM procedure to study if subjects' behavior in the quantity stage is consistent with these necessary conditions.

We proceed in the following manner. First, for each *history* in our dataset we only keep the static choices. All subjects make a quantity choice in period 1, but it is possible for example that the next period with a market choice is period 4. In our constrained dataset we would only keep the quantity stage choices for rounds 1 and 4 and would interpret them as the first and the second quantity choices. In this way we obtain a dataset that resembles the dataset coming from an infinitely repeated prisoners' dilemma. Second, we define a set of strategies  $K \subset \Sigma$  following the literature (see for example Dal Bó and Fréchette (2011) or Fudenberg et al. (2012)). We include in  $K$  five strategies that have been shown to capture most behavior in



infinitely repeated prisoners' dilemma: 1) Always Defect (AD), 2) Always Cooperate (AC), 3) Grim-Trigger (Grim), 4) Tit-for-Tat, and 5) Suspicious-Tit-for-Tat.<sup>56</sup>

	All data			Last 8 Supergames		
	$A_S$	$A_M$	$A_L$	$A_S$	$A_M$	$A_L$
AD	0.394*** (0.077)	0.403*** (0.096)	0.549*** (0.109)	0.463*** (0.114)	0.404*** (0.121)	0.604*** (0.154)
AC	0.064 (0.052)	0.094* (0.050)	0.024 (0.031)	0.123** (0.057)	0.124** (0.054)	0.026 (0.038)
Grim	0.205*** (0.088)	0.339*** (0.125)	0.047 (0.047)	0.172* (0.106)	0.335** (0.151)	0.000 (0.043)
Tit-for-Tat	0.285*** (0.088)	0.111 (0.083)	0.188 (0.126)	0.206* (0.128)	0.087 (0.103)	0.211* (0.128)
Susp.-Tit-for-Tat	0.052	0.052	0.192	0.036	0.048	0.158
$\gamma$	0.488*** (0.044)	0.419*** (0.054)	0.384*** (.033)	0.404*** (0.039)	0.357*** (0.051)	0.333*** (0.047)
$\beta$	0.885	0.916	0.931	0.922	0.943	0.953

Note: Significant at: \*\*\* 1%, \*\*5%, \*10%. See [Appendix C](#) for the definition of  $\gamma$ .  $\beta = \frac{1}{e^{(-1/\gamma)}}$

Table 16: Strategy frequency estimation method results

[Table 16](#) presents the results of the estimation for the three Standard treatments using all data and using the last eight super games.<sup>57</sup> The estimates uncover clear patterns in subjects' choices. Consider first always defect (AD). In all cases this is the strategy with the highest frequency, around 40% for  $A_S$  and  $A_M$  and close to 60% for  $A_L$ . Second, comparing across treatments we observe that Grim displays the opposite pattern of AD: while clearly non-existent for  $A_L$ , there is a large and significant mass in other cases.<sup>58</sup>

<sup>56</sup>In the cases of Tit-for-Tat and Suspicious-Tit-for-Tat from the second choice onwards the subject would simply select what the other chose the previous time, but these strategies differ in the period 1 choice. Tit-for-Tat starts by cooperating, while Suspicious-tit-for-tat starts with defection.

<sup>57</sup>We compute the standard deviations for the estimates bootstrapping 1000 repetitions. The procedure leaves unidentified the standard error for the  $K$ -th strategy. The estimate of  $\beta$  can be used to interpret how noisy the estimation is. For example, with only two actions a random draw would be consistent with  $\beta = 0.5$ . Notice that in all cases the estimate of  $\beta$  is relatively high, indicating that the set of strategies used for the estimation can accurately accommodate the data.

<sup>58</sup>The proportion corresponding to Grim is relatively higher for  $A_M$  than for  $A_S$ . This is consistent with cooperation being more attractive for  $A_S$ . It may be that attracted by the gains of cooperation subjects are more willing to forgive and start a new cooperative phase, which is feasible using Tit-for-Tat.

More importantly, notice that strategy AC displays a frequency estimate of approximately 12% that is significant for  $A_M$  and  $A_S$ . This is the frequency of successful cooperation. In other words, AC captures the mass that may be particularly influential in determining how strong the Markov assumption for structural estimation is. A strategy such as Grim or Tit-for-Tat can only be identified if subjects deviate from cooperation: along the cooperative phase both strategies are identical. But once subjects enter a punishment phase market behavior is closer to the stage Nash, and hence, discrepancies with respect to the MPE assumption for the quantity choice are only present for the periods prior to defection.

# Appendix D

## Robustness of Structural Estimates

Tables 17, 18, and 19 provide estimates of  $A$ ,  $B$ , and  $C$  as the session evolves. The first row in each table shows the estimates when we use all the sample (as reported in the text) and each row reports the estimation as we exclude earlier matches. The last row uses the last five matches of the session.

Overall the estimates for the medium and small market display relatively minor changes as the sample is restricted. We do notice some changes in the estimates of  $A$  and  $B$  in large market treatments. For the Standard treatment we notice a relatively large change when the sample is restricted to matches 9-16 and onwards. In the No Quantity Choice treatments we notice changes mainly in the estimate of  $B$  starting when the sample is restricted to matches 4-16. These changes in the estimates are consistent with the fact that in the large market treatments there are relatively few observations when both subjects are out of the market. As a session evolves the estimates rely on even fewer observations in this state.

Table 17: Sample used and estimates of  $A$

Matches included	$A_L$		$A_M$		$A_S$	
	Standard	No Quantity Choice	Standard	No Quantity Choice	Standard	No Quantity Choice
1-16	0.18	0.22	0.14	0.17	0.10	0.08
2-16	0.18	0.22	0.14	0.17	0.10	0.08
3-16	0.18	0.21	0.15	0.18	0.10	0.08
4-16	0.18	0.17	0.15	0.17	0.10	0.08
5-16	0.18	0.16	0.15	0.18	0.09	0.08
6-16	0.18	0.16	0.15	0.17	0.10	0.08
7-16	0.22	0.16	0.14	0.17	0.10	0.09
8-16	0.23	0.16	0.14	0.17	0.10	0.08
9-16	0.42	0.16	0.14	0.18	0.10	0.09
10-16	0.46	0.16	0.14	0.18	0.09	0.09
11-16	0.68	0.15	0.14	0.21	0.09	0.10

Table 18: Sample used and estimates of  $B$ 

Matches included	$A_L$		$A_M$		$A_S$	
	Standard	No Quantity Choice	Standard	No Quantity Choice	Standard	No Quantity Choice
1-16	0.11	0.22	0.05	0.19	0.07	0.20
2-16	0.10	0.20	0.05	0.19	0.07	0.20
3-16	0.10	0.19	0.06	0.19	0.07	0.20
4-16	0.10	0.08	0.07	0.19	0.07	0.19
5-16	0.09	0.07	0.05	0.19	0.07	0.17
6-16	0.09	0.07	0.06	0.18	0.09	0.17
7-16	0.20	0.07	0.04	0.18	0.09	0.19
8-16	0.22	0.06	0.05	0.19	0.09	0.19
9-16	0.71	0.05	0.06	0.20	0.09	0.21
10-16	0.78	0.07	0.05	0.23	0.06	0.22
11-16	1.33	0.04	0.04	0.28	0.04	0.25

Table 19: Sample used and Estimates of  $C$ 

Matches included	$A_L$		$A_M$		$A_S$	
	Standard	No Quantity Choice	Standard	No Quantity Choice	Standard	No Quantity Choice
1-16	0.54	0.56	0.55	0.47	0.53	0.43
2-16	0.55	0.56	0.55	0.47	0.53	0.43
3-16	0.55	0.57	0.56	0.46	0.52	0.44
4-16	0.56	0.56	0.56	0.47	0.52	0.43
5-16	0.55	0.57	0.55	0.48	0.52	0.44
6-16	0.56	0.58	0.57	0.48	0.52	0.45
7-16	0.56	0.58	0.58	0.48	0.52	0.45
8-16	0.57	0.57	0.58	0.47	0.52	0.45
9-16	0.54	0.57	0.57	0.47	0.52	0.46
10-16	0.55	0.57	0.57	0.46	0.53	0.46
11-16	0.52	0.58	0.57	0.43	0.53	0.46

## Robustness of Counterfactual Exercises

In this section we consider an alternative counterfactual experiment to measure the prediction bias due to collusion. We use the parameters we estimate for the Standard treatments and predict behavior in the No Quantity Choice treatments. We then contrast this prediction to actual behavior in No Quantity Choice treatments. The results are shown on [Table 20](#), where for a fixed value of  $A$  the baseline corresponds to the treatment with no quantity choice, and the counterfactual to the Standard treatment.

<b>Baseline/Counterfactual</b>	$A_S$	$A_M$	$A_L$
Standard/No Quantity Choice			
$A_S$	24.9 %	-	-
$A_M$	-	7.2 %	-
$A_L$	-	-	11.6 %

Table 20: Counterfactual Error From Collusion (MAPE(V)), Standard predicts No Quantity Choice

This table shows the resulting bias in counterfactual computations if the econometrician wrongly assumes that firms do not collude in the baseline (Standard treatment) and predicts the outcomes in a market (of the same market size) where firms do not collude. Then we contrast the prediction to actual behavior in the No Quantity Choice treatments and compute prediction errors.

The counterfactual bias varies from 7% to 25%. By definition, the highest incentives to collude are in the  $A_S$  market. Therefore, it is natural that the largest bias takes place in this case, where the magnitude means that averaging across states the difference between predicted continuation value and actual continuation value is 25%. On the one hand, a twenty-five percentage points bias in continuation values is relatively large. On the other hand, how large are these magnitudes relative to a case where firms fully collude in the baseline? To answer this question we perform a Monte Carlo exercise where in the baseline we generate data under full collusion and we estimate parameters under the assumption of no collusion. We then compare the prediction to counterfactual data where there is no collusion. Those results are shown in [Table 21](#)

These results show that the counterfactual bias due to collusion that we observe in the data is smaller than what would be observed if firms were successful at colluding. In the case of the small and medium market it is 11% to 12% of the maximal possible bias and in the large market it is 38% of the maximal possible bias. This means that especially in the scenario where

<b>Baseline/Counterfactual</b>	$A_S$ (Standard)	$A_M$ (Standard)	$A_L$ (Standard)
$A_S$ (No Quantity Choice)	197.1 %	-	-
$A_M$ (No Quantity Choice)	-	62.9 %	-
$A_L$ (No Quantity Choice)	-	-	30.2 %

Table 21: Maximal Counterfactual Error From Collusion, Standard predicts No Quantity Choice (**Monte Carlo Results**)

This table (based on Monte Carlo results and NOT data) shows the maximal resulting bias (measured by MAPE(V)) if the econometrician wrongly assumes that firms do not collude in the baseline and predicts the outcomes in a market (of the same market size) where firms do not collude.

the incentives to collude are high and where they should be quantitatively important we only observe a small fraction of the possible bias.

## Appendix E

One of the salient deviations from the theory in our data is that subjects do not enter and exit the market as often as the MPE predicts in this setting. [Table 3](#) summarizes the absolute difference between theoretical MPE probabilities and empirical probabilities across treatments. We refer to the absolute difference between MPE and empirical probabilities in the No Quantity Choice treatments as inertia. Average inertia (as measured in each treatment by the third column in [Table 3](#)) is comparable across No Quantity Choice treatments, ranging between 0.13 and 0.17.

In this appendix we describe three approaches to shed more light on inertia. In the first part of the appendix, we first study three alternative ways to explicitly account for inertia at the estimation stage. The goal is to obtain estimates closer to the true values. We will show that the three procedures actually lead to improvements. The first one directly corrects entry thresholds and uses the fact that we observe the actual thresholds that subjects pick. We then propose two different extended models that explicitly account for inertia and estimate an additional parameter (which do not require to observe the thresholds and could therefore be applied in a standard setting). The latter of the two is the most successful, and for this procedure we also report the full exercise on counterfactuals. We do document that counterfactual prediction errors are lower relative to the counterfactuals we report in the main text. However, the qualitative comparison between counterfactual prediction errors in Standard and No Quantity Choice treatment is qualitatively similar.

In the second part of the appendix we take a different approach and use Monte Carlo simulations to study how inertia affects parameter estimates. We show that inertia, for all reasonable ranges, biases the estimates of  $C$  (the entry cost) upwards and  $B$  (the competition parameter) downwards. However, the effect on  $A$  can be ambiguous. This is consistent with what we observe in the data.  $A$  is biased downwards in  $A_L$  and  $A_M$  but upwards in  $A_S$ . We illustrate with Monte Carlo simulations that the upwards bias in  $\hat{A}$  can result when inertia is mostly present in exit thresholds as in  $A_S$ .<sup>59</sup>

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<sup>59</sup>Notice that inspection of [Table 3](#) confirms this is the case in our data. That is, while the averages are similar, the presence of inertia in entry and exit thresholds changes with  $A$ . As  $A$  increases from  $A_S$  to  $A_L$  inertia shifts from exit to entry thresholds.

## E.1. Three Procedures to Account for Inertia at the Estimation Stage

### Subject-Specific Effects

We first explore to what extent we can recover estimates closer to the true parameter values by accounting for a subject-specific (“fixed-effect”) deviation from the theoretical threshold. Creating a dataset that controls for the average deviation from the MPE threshold of each subject would allow us to reduce the amount of inertia in the data and should result in estimates closer to the true values.

Recall that our experimental design asks subjects directly for their entry and exit thresholds (such thresholds, however, are typically not observed in a standard empirical application). The resulting binary entry and exit choices (which the estimation method uses) are computed based on those thresholds. To generate a dataset that controls for average deviations from theoretical predictions we proceed in three steps. We first compute a subject-specific mean deviation from the theoretically predicted ones. Second, we adjust each threshold by this amount. Finally, we compute a new set of entry-exit choices using the same random draws from the experimental sessions and the adjusted thresholds.<sup>60</sup> With this alternative dataset, based on “adjusted” entry/exit thresholds, we re-estimate the parameters. For comparability, the top panel of [Table 22](#) reproduces the main estimates in the paper, and the second panel shows the estimation results correcting for subject-specific effects.

What these results show is that this correction broadly moves all estimates in the right direction. Specifically, the entry cost  $C$  is substantially reduced, and the  $A$  estimates are moving in slightly closer to the true parameters. The estimate of  $B$  is also moving closer to the true value of 0.6 in almost all treatments, though it still is far from such value. Of course, correcting the data in this way is not feasible in a standard empirical application because (i) the thresholds are not directly observed and even if they were (ii) the theoretical thresholds are unknown.

### Inertia-Augmented Model

We now present our first augmented model that allows to partially correct for inertia without a priori knowledge of thresholds. Since our experiment was not designed to estimate such a

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<sup>60</sup>Of course, because the choices implied by adjusted thresholds and the thresholds selected by the subject may not coincide, this alternative data is no longer dynamically consistent. For example, using the adjusted thresholds we may compute that the firm exits in period  $t$ , but would be actually observed next period in the market because this is the state that actually occurred in the laboratory.



Treatment	Standard			No Quantity Choice		
	$A_S$	$A_M$	$A_L$	$A_S$	$A_M$	$A_L$
<b>Original (Reproduced from Table 4)</b>						
<i>A</i>	0.1	0.14	0.18	0.08	0.17	0.22
<i>B</i>	0.07	0.05	0.11	0.2	0.19	0.22
<i>C</i>	0.53	0.55	0.54	0.43	0.47	0.56
<b>Thresholds Corrected for Subject-Specific Effects</b>						
<i>A</i>	0.02	0.13	0.3	0.02	0.19	0.22
<i>B</i>	0.24	0.12	0.32	0.3	0.39	0.22
<i>C</i>	0.2	0.19	0.18	0.16	0.18	0.56
<b>Inertia-Augmented Model</b>						
<i>A</i>	0.08	0.12	0.15	0.07	0.15	0.29
<i>B</i>	0.07	0.05	0.1	0.52	0.19	0.43
<i>C</i>	0.18	0.18	0.19	0.25	0.16	0.18
<i>D</i>	0.01	0.01	0.01	0.01	0.1	0.01
<b>Myopic Inertia-Augmented Model</b>						
<i>A</i>	0.04	0.19	0.25	0.04	0.21	0.23
<i>B</i>	0.47	0.69	0.89	0.47	0.83	0.72
<i>C</i>	0.23	0.04	0.06	0.23	0.06	0.09
<i>D</i>	0.15	0.14	0.12	0.15	0.08	0.09

Table 22: Inertia: Parameter estimates

The top part of this table reproduces the parameter estimates of Table 4 and the bottom shows the estimates including inertia parameter  $D$ , which captures a potential time inconsistent behavior where the firm assumed that there is an entry or exit cost that has to be paid for changing the market status today but not at any point in the future. True values of parameters are:  $A_S = 0.05$ ,  $A_M = 0.25$ ,  $A_L = 0.4$ ,  $B = 0.6$ ,  $C = 0.15$ .

model, we see the model we introduce here and in the third approach as more speculative. An intuitive explanation for the observed behavior is that subjects perceive some general switching cost to change the market state. This would call for a straightforward extension of the model with one extra parameter, the perceived switching cost, that needs to be estimated. Unlike the entry cost it would have to be paid both for entering and exiting the market (this is, intuitively, also how it would be separately identified). We now present our first augmented model and start by re-writing the expressions that solve for the MPE recursively. For  $x \in \{0, 1\}$ , the following function captures the continuation value.

$$\Gamma(x, \mathbf{s}_t) = \sum_{\mathbf{s}_{t+1} \in \mathbf{S}} \int \max\{v^\alpha(0, \mathbf{s}_{t+1}) + \epsilon'(0), v^\alpha(1, \mathbf{s}_{t+1}) + \epsilon'(1)\} dG(\epsilon') F^\alpha(\mathbf{s}_{t+1}|x, \mathbf{s}_t) \forall \mathbf{s}_t \quad (9)$$

A first aspect to notice is that inertia can be thought of as working asymmetrically for a fixed agent  $i$ 's state. If agent  $i$  is in the market, which happens when the state is in set  $\mathbf{s}_t^1 = \{(1, 0), (1, 1)\}$ , then 'inertia' can be thought of as providing the agent an extra payment ( $D^1$ ) if the agent stays in the market, but not if the agent decides to leave. Likewise, if the agent is not in the market, that is if the state is in the set  $\mathbf{s}_t^0 = \{(0, 0), (0, 1)\}$ , then inertia would provide an extra payment ( $D^0$ ) if the agent stays out, a payment the agent would not receive if she chooses to enter. That is, the extra payments,  $D^0$  and  $D^1$  act by making it more expensive to leave the state in which the agent is located.

The recursive expressions that solve for MPE are given by:

$$v^\alpha(1, \mathbf{s}_t^1) = \Pi^\alpha(\mathbf{s}_t^1) + D^1 + \delta \cdot \Gamma(1, \mathbf{s}_t^1) \forall \mathbf{s}_t^1 \quad (10)$$

$$v^\alpha(1, \mathbf{s}_t^0) = \Pi^\alpha(\mathbf{s}_t^0) + \delta \cdot \Gamma(1, \mathbf{s}_t^0) \forall \mathbf{s}_t^0 \quad (11)$$

$$v^\alpha(0, \mathbf{s}_t^1) = \Pi^\alpha(\mathbf{s}_t^1) + \delta \cdot \Gamma(0, \mathbf{s}_t^1) \forall \mathbf{s}_t^1 \quad (12)$$

$$v^\alpha(0, \mathbf{s}_t^0) = \Pi^\alpha(\mathbf{s}_t^0) + D^0 + \delta \cdot \Gamma(0, \mathbf{s}_t^0) \forall \mathbf{s}_t^0 \quad (13)$$

Unfortunately, we cannot identify  $D^0$  separate from  $D^1$ , so we impose that  $D^0 = D^1 = D$ .<sup>61</sup>

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<sup>61</sup>As mentioned earlier, inertia is mostly present in exit thresholds when  $A$  is low ( $A_S$ ), but shifts towards entry thresholds as  $A$  increases to  $A_L$  (see Table 3). Thus, if it were possible to estimate  $D^0$  separately from  $D^1$ , the fit would be better. Our design was not planned to study inertia and our ability to structurally characterize inertia is thus limited.

Hence, the inertia-augmented model involves estimating one extra parameter ( $D$ ) and the estimates are presented in the third panel of [Table 22](#).

The estimate of parameter  $D$  is relatively small in all treatments. With respect to the parameters in the original model, we note a substantial drop of parameter  $C$ , which is closer to the true value in all treatments (relative to the original estimates). There are only small changes in the estimates of  $A$  and the estimates of  $B$ , while in most cases higher than in the original estimation, remain far from the true value. Even though such a model seems an intuitive alternative to capture inertia, it does not lead to a marked improvements of the estimates.

### Myopic Inertia-Augmented Model

The findings with the inertia-augmented model have lead us to explore another alternative, in which inertia is present but in a time-inconsistent manner. A possible justification behind this extension is that the agent considers a realized state differently than a potential state that can happen in the future. That is, if the agent is in the market, the agent has an “extra” valuation for the current state because that is what she has now. But when she considers the future, she doesn’t attach an “extra” valuation to being in the market tomorrow because that state has not yet materialized.

Since in this model inertia only affects the valuation in the present, we can re-express the continuation values as follows:

$$v^\alpha(x, \mathbf{s}_t) = \Pi^\alpha(\mathbf{s}_t) + \delta \cdot \Gamma(x, \mathbf{s}_t) \forall \mathbf{s}_t \quad (14)$$

for  $x \in \{0, 1\}$ .

However, the current valuations are affected by inertia. We express the value functions of a problem with myopic inertia as follows.

$$\tilde{v}^\alpha(1, \mathbf{s}_t^1) = \Pi^\alpha(\mathbf{s}_t^1) + D^1 + \delta \cdot \Gamma(1, \mathbf{s}_t^1) \forall \mathbf{s}_t^1 \quad (15)$$

$$\tilde{v}^\alpha(1, \mathbf{s}_t^0) = \Pi^\alpha(\mathbf{s}_t^0) + \delta \cdot \Gamma(1, \mathbf{s}_t^0) \forall \mathbf{s}_t^0 \quad (16)$$

$$\tilde{v}^\alpha(0, \mathbf{s}_t^1) = \Pi^\alpha(\mathbf{s}_t^1) + \delta \cdot \Gamma(0, \mathbf{s}_t^1) \forall \mathbf{s}_t^1 \quad (17)$$

$$\tilde{v}^\alpha(0, \mathbf{s}_t^0) = \Pi^\alpha(\mathbf{s}_t^0) + D^0 + \delta \cdot \Gamma(0, \mathbf{s}_t^0) \forall \mathbf{s}_t^0 \quad (18)$$

We cannot identify  $D^0$  separate from  $D^1$ . Since we know that inertia is mostly present in exit threshold in  $A_S$  (see [Table 3](#)), we estimate  $D^1 = D$ ,  $D^0 = 0$  in  $A_S$ . Inertia shifts towards entry thresholds in  $A_M$  and  $A_L$ , so we estimate  $D^0 = D$ ,  $D^1 = D$  in these two treatments.<sup>62</sup>

We estimate  $D$  together with the other parameters using a slight modification to the estimation procedure described on [Appendix A](#). We start with some initial values for all parameters and compute the system of equations in (9)-(14). In addition, we use (9)-(14) and the initial guesses to compute (15)-(18). We then use (9)-(14) to compute predicted choice probabilities that we contrast to observed choice probabilities. The procedure is repeated until the parameter estimates provides predicted choice probabilities that are sufficiently close to the observed choice probabilities.

The bottom panel of [Table 22](#) provides the estimates. The estimate of parameter  $D$  varies from 0.05 to 0.15, depending on the treatment. With respect to the parameters in the original model, we also note a substantial drop of parameter  $C$ , consistent with all corrections for inertia (and the Monte Carlo exercises we report in the next section). As with other corrections, the changes in estimates of  $A$  are more nuanced, but there is a large upward adjustment in parameter  $B$ , which is closer to the true value of 0.6 in all treatments. Without controlling for inertia the parameter is substantially underestimated, with values between 0.05 and 0.22 and none of the previous corrections is very successful in bringing the estimate close to the true value.<sup>63</sup>

Given that the myopic augmented-inertia model is relatively more successful in moving all estimates closer to the true values, we inspect it further and use it to report counterfactual predictions. The two top panels of [Table 22](#) reproduce, as a reference, the predictions for counterfactuals that we report in the text. The two bottom panels provide the same computations, but using the myopic augmented-inertia model.

A first observation is that in 10 of 12 predictions, the myopic inertia-augmented model involves a lower prediction error than the original model reported in the text.<sup>64</sup> This suggests that controlling for inertia can indeed reduce the prediction error. A second observation is that while the prediction error is reduced in the majority of cases, there is no indication of higher prediction error in the Standard treatments relative to the No Market Choice treatments. This

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<sup>62</sup>An empirical researcher would not have information related to which thresholds are mostly affected by inertia, but the purpose of this exercise is to provide an estimation that explicitly controls for inertia as well as possible.

<sup>63</sup>The Monte Carlo exercises in the next section will show that inertia biases the parameter  $B$  downwards.

<sup>64</sup>In the two cases where the prediction is higher in the myopic inertia-augmented model, the increase in the error is relatively small. From 0.38 to 0.39 when the  $A_L$  Standard is the baseline and  $A_M$  Standard the predicted counterfactual, and from 0.52 to 0.67 when the  $A_M$  No Market Choice is the baseline and  $A_S$  No Market Choice the predicted counterfactual.

suggests that the possibility of collusion is not leading to an increase in the prediction error when we control for inertia. In a few words, the main comparative static that we report in the paper for counterfactual exercises holds when we use the myopic inertia-augmented model.<sup>65</sup>

<b>Baseline/Counterfactual</b>	$A_S$	$A_M$	$A_L$
<b>Standard</b>			
$A_S$	-	621.8	949.1
$A_M$	65.1	-	82.3
$A_L$	68.5	37.8	-
<b>No Market Choice</b>			
$A_S$	-	326.4	716.2
$A_M$	51.6	-	84.3
$A_L$	64.9	40.8	-
<b>Standard (Myopic Inertia)</b>			
$A_S$	-	96.9	98.3
$A_M$	65.4	-	43.9
$A_L$	66.1	35.3	-
<b>No Market Choice (Myopic Inertia)</b>			
$A_S$	-	29.3	30.7
$A_M$	42.7	-	70.2
$A_L$	50.3	39.2	-

Table 23: Counterfactual prediction error

This table shows the counterfactual predictions using the MAPE( $V$ ) measure if we account for inertia by using the myopic inertia-augmented model.

## E.2. Monte Carlo Study on Inertia

In this section we use a series of Monte Carlo exercises to study how differences between observed probabilities and MPE probabilities can affect the estimates. We first provide an

<sup>65</sup>The counterfactual exercise we report here does not fully remove inertia from counterfactual prediction errors. We conduct the counterfactual exercise scaling the  $A$  estimate and keeping the estimates of  $B$ ,  $C$  and  $D$  from the baseline. As explained earlier, at the estimation stage we assume that the researcher knows that inertia operates mostly through exit thresholds in  $A_S$  and through both thresholds in other treatments. But for the counterfactual exercise we keep the estimate of  $D$  from the baseline. Since inertia can operate differently in baseline and counterfactual, the difference in counterfactual prediction errors can still capture some effect from inertia.

informal discussion on the identification of each coefficient that we illustrate with simulations. In a second step we outline how inertia affects the estimates in each of our treatments. What we document is consistent with our findings in the previous section. In particular, inertia will bias the estimate of  $C$  upwards and  $B$  downwards.

Table 24 reports several Monte Carlo simulations that connect entry-exit probabilities and coefficient estimates. The baseline reference is simulation 0. The data for the simulation is generated according to probabilities in the first four columns.<sup>66</sup> These probabilities correspond to the MPE equilibrium in the  $A_M$  treatment, and as shown in the last three columns of the Monte Carlo simulation, recovers the true parameters of this treatment. We now illustrate how small optimization errors can generate a bias in each coefficient.

We start with the estimate of  $A$ . Notice first that the structural procedure assigns a quantity-stage contemporaneous payoff that includes  $A$  whenever the subject is in the market.<sup>67</sup> This suggests that the estimate of  $A$  will be large if subjects display a high propensity to be in the market next period regardless of the state. Consider simulations 1 and 1' of Table 24. In the case of simulation 1 (1') the data is generated with probabilities equal to those of simulation 0 minus (plus) 0.05. In other words, being in the market next period is less (more) likely for all states in simulation 1 (1'). In line with the intuition, the estimate for  $A$  in simulation 1 (1') is below (above) the estimate in simulation 0.

Parameter  $B$  captures the effect of competition. Intuitively,  $\hat{B}$  is identified from comparing the subject's choices depending on whether the other is in the market or not; that is,  $p(1, 0) - p(1, 1)$  and  $p(0, 0) - p(0, 1)$ . In principle, the larger these differences the more the subject reacts to the presence of the other in the market, which means that the effect of competition is larger and the estimate of  $B$  will be correspondingly higher. This intuition is confirmed by simulations 2 and 2'. Notice that in the baseline simulation 0 the difference in probabilities is 0.1 in both cases.<sup>68</sup> In simulation 2 (2') we reduce (increase) the difference in probabilities to 0.05 (0.15) and accordingly observe a reduction (increase) in  $\hat{B}$  relative to the baseline.

Finally, the estimate of  $C$  will be high when the probabilities indicate that subjects do not want to pay the fixed fee to enter the market, which is consistent with subjects being very likely to remain in the market if they are already in the market and to stay out if they are already out.

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<sup>66</sup>For each simulation we proceed as described in section 4. We assume that there are 300 pairs of firms, and generate 100 data sets (according to the probabilities described in the table) that we use to estimate parameters.

<sup>67</sup>Recall that the quantity-stage contemporaneous payoff when the subject is in the market is  $100 \times (2A + 0.60)$  if the other is out and  $100 \times (2A - B + 0.60)$  if the other is also in. Meanwhile the quantity-stage payoff when the subject is out of the market is  $100 \times 0.6$ .

<sup>68</sup> $p(1,0)-p(1,1)=0.70-0.60=0.1$ ;  $p(0,0)-p(0,1)=0.50-0.40=0.1$ .

In other words, the estimate  $\hat{C}$  is large if there is a large difference between probabilities when the subject is in the market ( $p(1, \cdot)$ ) and probabilities when the subject is out of the market ( $p(0, \cdot)$ ). In simulation 3 (3') we subtract (add) 0.05 to  $p(1, \cdot)$  simulation 0 probabilities and add (subtract) 0.05 to  $p(0, \cdot)$  simulation 0 probabilities. Correspondingly, we find a lower (higher) estimate of  $C$  in simulation 3 (3') relative to the baseline.

Table 24: Monte Carlo simulations and optimization errors

Simulation	Probabilities				Estimates		
	$p(1, 0)$	$p(1, 1)$	$p(0, 0)$	$p(0, 1)$	$\hat{A}$	$\hat{B}$	$\hat{C}$
0	0.70	0.60	0.50	0.40	0.25	0.60	0.15
1	0.65	0.55	0.45	0.35	<b>0.21</b>	0.60	0.15
1'	0.75	0.65	0.55	0.45	<b>0.41</b>	0.50	0.16
2	0.65	0.60	0.45	0.40	0.16	<b>0.28</b>	0.19
2'	0.75	0.60	0.55	0.40	0.34	<b>0.91</b>	0.08
3	0.65	0.55	0.55	0.45	0.43	1.17	<b>0.01</b>
3'	0.75	0.65	0.45	0.35	0.20	0.40	<b>0.26</b>
4	0.95	0.85	0.44	0.40	<b>0.33</b>	0.01	1.47
5	0.80	0.60	0.50	0.30	0.27	<b>0.77</b>	0.17

Note:  $p(s)$  indicates the probability of being in the market next period conditional on being in state  $s$  in the current period.

Now, we use Monte Carlo simulations to evaluate how inertia can affect the estimates. Suppose that MPE probabilities are given by  $\mathbf{p}$ . We say that  $\mathbf{p}'$  exhibits inertia relative to  $\mathbf{p}$  if  $p'(1, \cdot) > p(1, \cdot)$  and  $p'(0, \cdot) < p(1, \cdot)$ . Notice that the exercise described in simulation 3' precisely involves the deviation from simulation 0 probabilities introduced by inertia. Inertia makes transitions between states more rare and is always rationalized with a higher estimate of  $\hat{C}$ .

With respect to the estimates of  $A$  and  $B$  inertia can introduce an upwards or downwards bias. The case presented in simulation 3' shows a downwards bias in  $\hat{A}$  relative to simulation 0 (0.20 vs. 0.40). This downwards bias in  $\hat{A}$  is consistent with the estimates for  $A_L$  and  $A_M$

reported in [Table 4](#). In these two treatments there is evidence of inertia in probabilities related to both entry and exit thresholds. In the  $A_S$  treatment inertia is present almost exclusively in probabilities related to exit thresholds ( $p(1, \cdot)$ ). Simulation 4 reproduces some of the inertia conditions present in the  $A_S$  treatment. Relative to the simulation 0 baseline, we add 0.25 to both probabilities related to exit thresholds, and subtract 0.06 from  $p(0, 0)$ .<sup>69</sup> In this case, there is an upwards bias in  $\hat{A}$  (0.33 vs. 0.25). Clearly, the equilibrium MPE probabilities in  $A_S$  differ from those in the simulation 0 baseline, but we observe a similar effect in the estimates, in particular, with  $\hat{A}$  biased upwards.

In all  $\hat{B}$  reported in [Table 4](#) there is a downwards bias relative to the true  $B$  parameter. This is also consistent with the reports in simulations 3' and 4 that also involve inertia. Although we do not observe it in our data, it is possible to introduce inertia in a way that would bias  $B$  upwards. Simulation 5 involves a change in probabilities relative to simulation 0 that is consistent with inertia, but the 'inertia' in  $p(1, 0)$  and  $p(0, 1)$  is larger than the inertia in  $p(1, 1)$  and  $p(0, 0)$ . In other words, inertia increases how one subject responds to the presence of the other in the market. In this case, we observe an upwards bias in  $\hat{B}$  (0.77 vs. 0.60).

We conclude this section with another set of Monte Carlo simulations that focus on how the presence of inertia can bias the coefficients for different levels of collusion. As in [section 4](#), the data are generated from a model in which a proportion  $x \in [0, 1]$  of the pairs of firms collude. We use the setup of the  $A_M$  treatment, but add (subtract) 0.14 points to exit (entry) threshold probabilities. In other words, the exercise reported in [Figure 9](#) is comparable to [Figure 1](#) except that it includes inertia in the data. The main observations remain unchanged: the estimates of  $A$  and  $C$  are basically unaffected by the presence of collusion, which does affect the estimate of  $B$ , biasing it downwards as collusion increases.

## Counterfactuals

[Table 25](#) and [Figure 10](#) provide further details of the counterfactual predictions presented in [subsection 5.3](#). [Table 25](#) presents the predictions for  $p(s)$  for the counterfactual exercise reported in [Table 5](#) (predicted 1) and the second exercise reported in [Table 6](#) (predicted 2). The table also displays actual observed probabilities in each case. [Figure 10](#) shows the actual probabilities and the predictions for the first counterfactual exercise (see [Table 5](#)).

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<sup>69</sup>As a consequence there is only a small difference between probabilities related to entry thresholds, which is consistent with what we find for  $A_S$  (see [Appendix B](#)).



<i>Baseline <math>A_L</math></i>							
	state	$A_S$			$A_M$		
		predicted 1	predicted 2	actual	predicted 1	predicted 2	actual
<i>Standard</i>	$p(1, 0)$	0.56	0.74	0.76	0.79	0.87	0.88
	$p(1, 1)$	0.50	0.68	0.71	0.72	0.80	0.85
	$p(0, 0)$	0.02	0.21	0.21	0.24	0.31	0.34
	$p(0, 1)$	0.00	0.15	0.20	0.18	0.24	0.30
<i>No Quantity</i>	$p(1, 0)$	0.58	0.66	0.71	0.87	0.87	0.87
	$p(1, 1)$	0.47	0.59	0.54	0.72	0.76	0.77
	$p(0, 0)$	0.01	0.21	0.18	0.27	0.37	0.37
	$p(0, 1)$	0.00	0.12	0.17	0.12	0.26	0.29
<i>Baseline <math>A_M</math></i>							
	state	$A_S$			$A_L$		
		predicted 1	predicted 2	actual	predicted 1	predicted 2	actual
<i>Standard</i>	$p(1, 0)$	0.58	0.76	0.76	1.00	0.98	0.95
	$p(1, 1)$	0.55	0.73	0.71	1.00	0.95	0.89
	$p(0, 0)$	0.03	0.23	0.21	0.55	0.44	0.38
	$p(0, 1)$	0.00	0.20	0.20	0.53	0.41	0.34
<i>No Quantity</i>	$p(1, 0)$	0.59	0.66	0.71	1.00	1.00	0.94
	$p(1, 1)$	0.49	0.58	0.54	0.97	0.89	0.89
	$p(0, 0)$	0.09	0.22	0.18	0.57	0.45	0.43
	$p(0, 1)$	0.01	0.14	0.17	0.50	0.33	0.31
<i>Baseline <math>A_S</math></i>							
	state	$A_M$			$A_L$		
		predicted 1	predicted 2	actual	predicted 1	predicted 2	actual
<i>Standard</i>	$p(1, 0)$	1.00	0.88	0.88	1.00	0.97	0.95
	$p(1, 1)$	1.00	0.83	0.85	1.00	0.93	0.89
	$p(0, 0)$	1.00	0.34	0.34	1.00	0.43	0.38
	$p(0, 1)$	1.00	0.28	0.30	1.00	0.39	0.34
<i>No Quantity</i>	$p(1, 0)$	1.00	0.87	0.87	1.00	1.00	0.94
	$p(1, 1)$	1.00	0.77	0.77	1.00	0.91	0.89
	$p(0, 0)$	0.81	0.37	0.36	1.00	0.45	0.43
	$p(0, 1)$	0.78	0.28	0.29	1.00	0.33	0.31

Notes: Predicted 1 (Predicted2) presents probabilities related to the counterfactual exercise reported in [Table 5](#) ([Table 6](#)).

Table 25: Counterfactual calculations

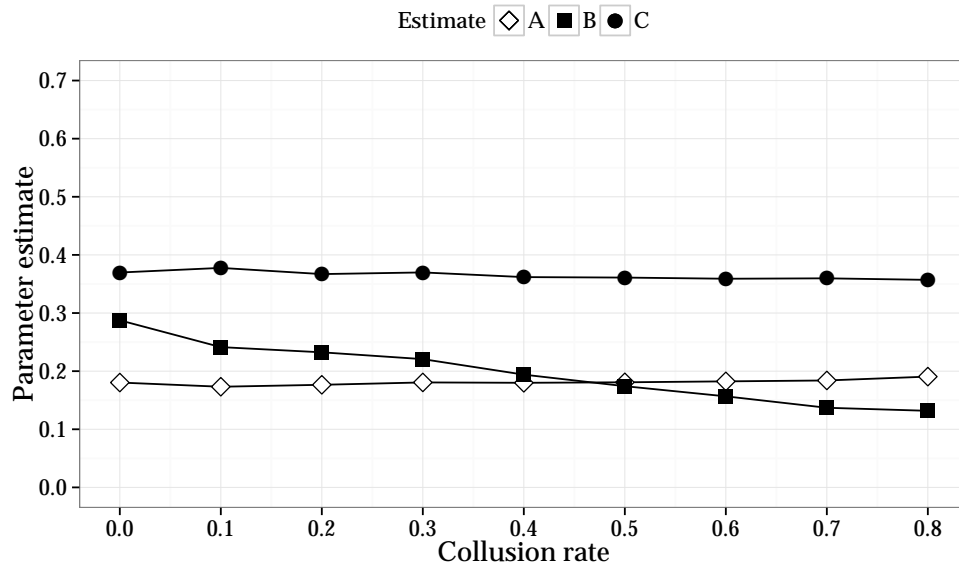
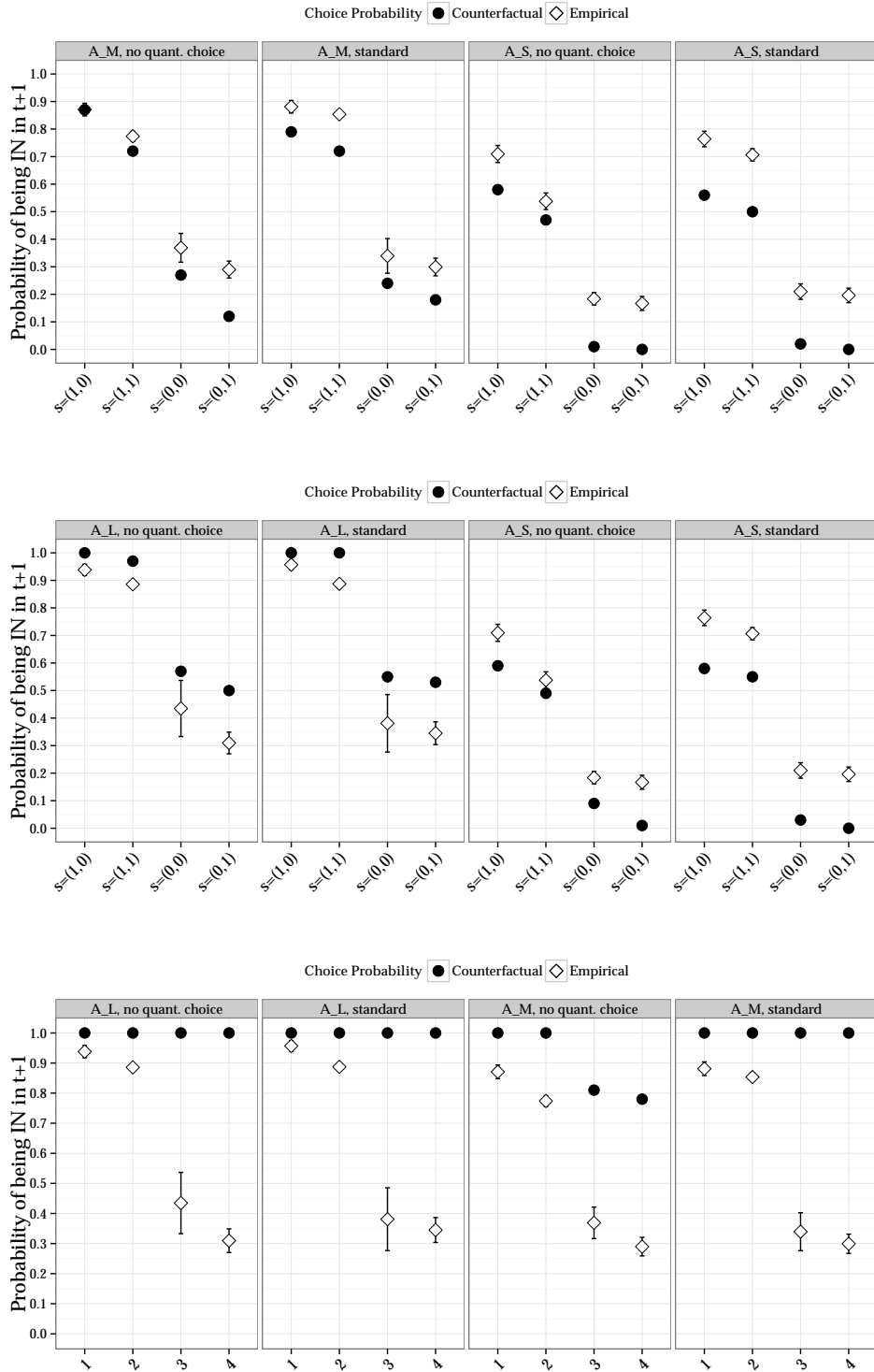


Figure 9: Parameter estimates under different collusion probabilities for the  $A_M$  treatment with inertia.

Table 26 provides information on counterfactual calculations of the probability of observing a monopoly or a duopoly using the counterfactual exercise reported in Table 5.



Baseline treatments: Row 1- $A_L$ , Row 2- $A_M$ , Row 3- $A_S$

Figure 10: Counterfactual predictions

<i>Baseline <math>A_L</math></i>							
	probability	$A_L$		$A_S$		$A_M$	
		predicted	actual	predicted	actual	predicted	actual
<i>Standard</i>	$p_2$	0.72	0.74	0.00	0.24	0.26	0.61
	$p_1$	0.24	0.23	0.04	0.35	0.38	0.29
<i>No Quantity</i>	$p_2$	0.74	0.71	0.00	0.13	0.25	0.50
	$p_1$	0.25	0.25	0.03	0.32	0.47	0.35
<i>Baseline <math>A_M</math></i>							
	probability	$A_M$		$A_S$		$A_L$	
		predicted	actual	predicted	actual	predicted	actual
<i>Standard</i>	$p_2$	0.57	0.61	0.00	0.24	1.00	0.74
	$p_1$	0.30	0.29	0.03	0.35	0.00	0.23
<i>No Quantity</i>	$p_2$	0.49	0.50	0.01	0.13	0.94	0.71
	$p_1$	0.36	0.35	0.18	0.32	0.06	0.25
<i>Baseline <math>A_S</math></i>							
	probability	$A_S$		$A_M$		$A_L$	
		predicted	actual	predicted	actual	predicted	actual
<i>Standard</i>	$p_2$	0.24	0.24	1.00	0.61	1.00	0.74
	$p_1$	0.35	0.35	0.00	0.29	0.00	0.23
<i>No Quantity</i>	$p_2$	0.12	0.13	0.04	0.50	1.00	0.71
	$p_1$	0.32	0.32	0.23	0.35	0.00	0.25

Table 26: Counterfactual calculations for the probability of observing a monopoly ( $p_1$ ) or a duopoly ( $p_2$ )

## Appendix F

This appendix describes several additional details of the experimental implementation. We implement the infinite time horizon as an uncertain time horizon (Roth and Murnighan, 1978). After each period of play, there is one more period with probability  $\delta = 0.8$ . We implement the uncertain time horizon using a modified block design (Fréchette and Yuksel, 2013). Subjects play the first five periods without being told after each period whether the supergame has ended or not. Once period five ends they are informed whether the game ended in any of the first five periods. Only periods prior to ending count for payoff (including the period when the game ended). From the sixth period onwards subjects are told period by period whether the game ended or not, and cumulative payoffs are computed for all periods until the game ends. This procedure allows us to collect information for several periods without affecting the theoretical incentives.<sup>70</sup>

Our sessions are divided into two parts. The difference between parts is in how subjects report their dynamic choice to the interface. In Part 1, in the exit (entry) stage subjects are informed of the randomly selected exit payment (entry fee) and then decide whether to exit or not (enter or not). In Part 2 subjects first specify an exit threshold (entry threshold), that is a number between  $[0, 100]$ , with the understanding that if the exit payment is higher than the threshold (entry fee is lower than the threshold) they will exit the market (enter the market).<sup>71</sup> Part 1 consists of 1 supergame and Part 2 consists of the remaining 15 supergames.<sup>72</sup>

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<sup>70</sup>See Fréchette and Yuksel (2013) for a comparison between this and other alternatives to implement infinite time horizons in the laboratory.

<sup>71</sup>Appendix C presents the instructions, screenshots of the interface and describes how subjects made their choices. In the case of the entry fee subjects specify a threshold in  $[15, 115]$ , which includes the fixed portion of the entry fee. For the purpose of analysis in the paper we will always present entry thresholds net of the fixed entry fee.

<sup>72</sup>The structural estimation procedure uses only information on whether subjects are in the market or not for estimation. Our implementation in part 2 provides us with additional information: we know the threshold of their decision. We use the additional information to evaluate the aggregate information content of only using the binary information for being in the market or not. We find the binary information to be consistent with thresholds if aggregate estimates on frequencies per state are of a comparable magnitude. If this were not the case, then using only binary information may already introduce a bias in the estimation. However, in the data we do not find that using only whether firms are in the market or not would lead to a bias.

## Appendix G

This appendix provides the instructions for the Standard treatment for  $A_L$ . The instructions consist of two parts. The first part presents the environment for the first cycle, and part 2 introduces the thresholds for entry/exit decisions. Instructions for No Quantity Choice treatments are identical except that we do not present a table for the quantity choice decision, and instead subjects are told they would receive Nash payoff when they are both in the market. After the instructions there is a set of figures with screen shots of the interface.

### INSTRUCTIONS

Welcome

You are about to participate in an experiment on decision-making. What you earn depends partly on your decisions, partly on the decisions of others, and partly on chance. Please turn off cell phones and similar devices now. Please do not talk or in any way try to communicate with other participants. We will start with a brief instruction period. During the instruction period you will be given a description of the main features of the experiment. If you have any questions during this period, raise your hand and your question will be answered so everyone can hear.

#### General Instructions: Part 1

1. This experiment is divided into 16 cycles. In each cycle you will be matched with a randomly selected person in the room. In each cycle, you will be asked to make decisions over a sequence of rounds.
2. The number of rounds in a cycle is randomly determined as follows:
  - After each round, there is an 80% probability that the cycle will continue for at least another round of payment.
  - At the end of each round the computer rolls a 100-sided die.
  - If the number is equal to or smaller than 80, there will be one more round that will count for your payments.
  - If the number is larger than 80, then subsequent rounds stop counting toward your payment.

- For example, if you are in round 2, the probability that the third round will count is 80%. If you are in round 9, the probability round 10 also counts is 80%. In other words, at any point in a cycle, the probability that the payment in the cycle continues is 80%.
3. You interact with the same person in all rounds of a cycle. After a cycle is finished, you will be randomly matched with a participant for a new cycle. In each round, your payoff depends on your choices and those of the person you are paired with. In each round there is a market stage and an entry/exit stage. In the entry/exit stage you and the other will decide whether to enter or exit the market. We first explain the market stage and later we explain the entry/exit stage.
  4. At the beginning of each cycle (in Round 1) you and the other start in the market. You and the other will first make the market stage choices and then decide whether you want to stay in the market or exit.

**Market Stage**

5. When you and the other are both in the market, your payoff depends on your choice and the choice of the other:
  - If you select 1, and the other selects 1, your payoff is 100, and the other's is 100.
  - If you select 1, and the other selects 2, your payoff is 40, and the other's is 140.
  - If you select 2, and the other selects 1, your payoff is 140, and the other's is 40.
  - If you select 2, and the other selects 2, your payoff is 80, and the other's is 80.

The table below summarizes all the possible outcomes:

		Other's Choice	
		1	2
Your Choice	1	100, <i>100</i>	40, <i>140</i>
	2	140, <i>40</i>	80, <i>80</i>

In this table, the rows indicate your choices and the columns the choices of the person you are paired with. The first number of each cell represents your payoff, and the second number (in italics) is the payoff of the person you are paired with.

6. If in any round you are in the market and the other is out, your payoff will be equal to 140.
7. If in any round you are out of the market you make a payoff of 60.
8. Once the market stage is over, you will start the entry/exit stage.

### **Entry/Exit Stage**

9. Exit decision. In each round when you are in the market, you will have to decide whether you want to exit the market or not. If you exit the market you will receive an exit payment. The exit payment is a random number between 0 and 100. All numbers are equally likely. The randomly selected exit payment will be presented to you on the screen. You will have to indicate whether you want to take the exit payment and exit the market or not take the payment and stay in the market.
10. The exit payment is selected separately for each participant. That means that you will have one exit payment and when the other is selecting whether to exit or not, they will have another randomly selected exit payment. The exit payment is selected randomly in each round. This means that exit payments in different rounds will likely be different.
11. Entry decision. If in any round you are out of the market, you have to choose whether you want to enter the market or not. To enter the market you have to pay an entry fee. The entry fee is a random number between 15 and 115. All numbers are equally likely. The randomly selected entry fee will be presented to you on the screen. You will have to indicate whether you want to pay the entry fee and enter the market or not pay the fee and stay out of the market.
12. The entry fee is selected separately for each participant. That means that you will have one entry fee and when the other is selecting whether to enter or not, they will have another randomly selected entry fee. The entry fee is selected randomly in each round. This means that entry fees in different rounds will likely be different.
13. In each round after round 1 you first face the market stage and then the entry/exit stage. If you are in the market in that round you will have to decide whether to exit or not. If you are out of the market you will have to decide whether to enter or not.

### **Payoffs**



14. In each cycle you start with 30 points, and you will make choices for the first 5 rounds without knowing whether or not the cycle payment has stopped. At the end of the fifth round the interface will display on the screen the results of the 100-sided die roll for each of the first 5 rounds.
15. If the roll of the 100-sided die was higher than 80 for any of the first five rounds, the cycle will end, and the last round for payment is the first where the 100-sided die roll is higher than 80.
  - The interface subtracts entry fees that you pay, adds exit payments, and adds all points that you make in the market stages of all rounds that count for payment within a cycle.
  - For example, assume that the 100-sided die in the first five rounds results in: 40, 84, 3, 95, 65. Because 84 is higher than 80, payments will stop after the second round. The interface will add your market and entry/exit payoffs for rounds 1 and 2.
16. If the 100-sided die rolls were lower than or equal to 80 for the first five rounds, there will be a sixth round. From the sixth round onwards the interface will display the 100-sided die roll round by round. The cycle will end in the first round where the 100-sided die roll is higher than 80.
  - The interface subtracts entry fees that you pay, adds exit payments, and adds all points that you make in the market stages of all rounds that count for payment within a cycle.
  - For example, assume that the 100-sided die in the first five rounds results in: 51, 24, 13, 80, 55. Because all numbers are equal to or lower than 80 there will be another round, so the cycle continues to round 6. After you make your choices for round 6 you are shown that the 100-sided die for that round is 52, which is lower than 80 so there will be a seventh round. After round 7 you are shown that the 100-sided die for that round is 91. Because 91 is higher than 80 the cycle is over and the interface will add your payoffs for all rounds 1 through 7.
17. If at any point in the cycle your total payoff for the cycle is less than 0, the cycle is over.

18. Your total payoffs for the session are computed by adding the total payoffs of all 16 cycles. These payoffs will be converted to dollars at the rate of 0.0025\$ for every point earned.

Are there any questions?

**Summary**

Before we start, let me remind you that:

- The length of a cycle is randomly determined. After every round there is an 80% probability that the payment cycle will continue for another round.
- In Round 1 of each cycle you and the other start in the market.
- Each Round has a market stage and an entry/exit stage.

1. Market Stage Payoffs

		Other	
		In the Market	Out of the Market
You	In the Market	See Payoff Table	140
	Out of the Market	60	60

2. Exit/Entry Decision

- If you are out and decide to enter, you will pay the entry fee. If you stay out, you do not have to pay any fee.
- If you are in and decide to leave, you will be paid the exit payment. If you decide to stay in, you will not receive an extra payment.
- You interact with the same person in all rounds of a cycle. After a cycle is finished, you will be randomly matched with a participant for a new cycle.
- Part 1 consists of 1 cycle. Once the first cycle is over we will give you brief instructions for Part 2 that will consist of 15 cycles. The only difference between Part 1 and Part 2 will be on how you report your choices to the interface. Other than that Part 1 and Part 2 are identical.

## General Instructions: Part 2

1. The only difference in Part 2 is on how you report to the interface your entry/exit decisions.

### Exit Decision

2. Instead of deciding if you want to Exit or Stay In the market for a particular Exit Payment, you will report an Exit Threshold.
3. You will report your Exit Threshold before you learn the Exit Payment that was randomly selected.
4. The Exit Threshold specifies the minimum Exit Payment you would take to exit the market. If the Exit Payment were to be higher than your choice for the Exit Threshold, then you would exit the market and receive the Exit Payment. If the Exit Payment were to be equal to or lower than your choice for the Exit Threshold, then you will Stay In the market and not receive the Exit Payment.
5. After you submit your choice for the Exit Threshold the interface will show you the randomly selected Exit Payment and will implement a choice for your Exit Threshold.

### Entry Decision

6. Instead of deciding if you want to Enter or Stay Out of the market for a particular Entry Fee, you will report an Entry Threshold.
7. You will report your Entry Threshold before you learn the Entry Fee that was randomly selected.
8. The Entry Threshold specifies the maximum Entry Fee below which you are willing to pay to enter the market. If the Entry Fee were to be higher than or equal to your choice for the Entry Threshold, then you would not enter the market and not pay the Entry Fee. If the Entry Fee were to be lower than your choice for the Entry Threshold, then you would enter the market and pay the Entry Fee.
9. After you submit your choice for the Entry Threshold the interface will show you the randomly selected Entry Fee and will implement a choice for your Entry Threshold.

Are there any questions?

## Screenshots of the Interface

Figure 11 displays the first screen that subjects see when the experiment starts in the case of a Standard treatment with  $A = 0.4$ . At the top left subjects are reminded of general information: the cycle and rounds within the cycle. The blank part on the left side of the screen will be populated with past decisions as the session evolves. In round 1 of every cycle both start in the market, which they are reminded of at the top right. The quantity stage table is presented below and subjects are asked to select a row. In the laboratory we refer to the quantity stage as the market stage.

Figure 12 shows a case where the first row has been selected. As soon as a row is selected a 'submit' button appears. Subjects can change their choice as long as they haven't clicked on the 'submit' button. Figure 13 shows an example of the feedback subjects get in a case where the subject selected row 2 and the other selected row 1.

After a quantity stage subjects face the entry/exit stage. Figure 14 shows an example of an exit stage in cycle 1. Subjects are presented with a randomly selected scrap value and they simply indicate if they exit or stay in the market. An entry stage is similar, except that subjects decide between 'enter' or 'stay out.'

Figure 15 shows an example when there is no quantity decision in the quantity stage. Subjects in this case are simply informed of their quantity stage payoff. This screen is qualitatively similar to what subjects in the No Quantity Choice treatment see if they are both in the market. This screenshot, which corresponds to a case in round 5, also shows on the left side the table with past decisions in the current cycle. As the session evolves subjects also have access to choices for previous cycles. They simply enter the number for the cycle for which they wish to see their feedback in the box after 'History for Cycle' and click on 'Show.'

Cycle: 1		Round: 1	
<b>Market Stage: You In, Other In</b>			
Please select a row			
The Other's Choice			
		1	2
Your Choice	1	100, 100	40, 140
	2	140, 40	80, 80

Figure 11: Quantity Stage of Standard Treatment with  $A = 0.4$ .

Cycle: 1		Round: 1	
<b>Market Stage: You In, Other In</b>			
Please select a row			
The Other's Choice			
		1	2
Your Choice	1	100, 100	40, 140
	2	140, 40	80, 80
<input type="button" value="Submit"/>			

Figure 12: Example where the subject selects row 1.

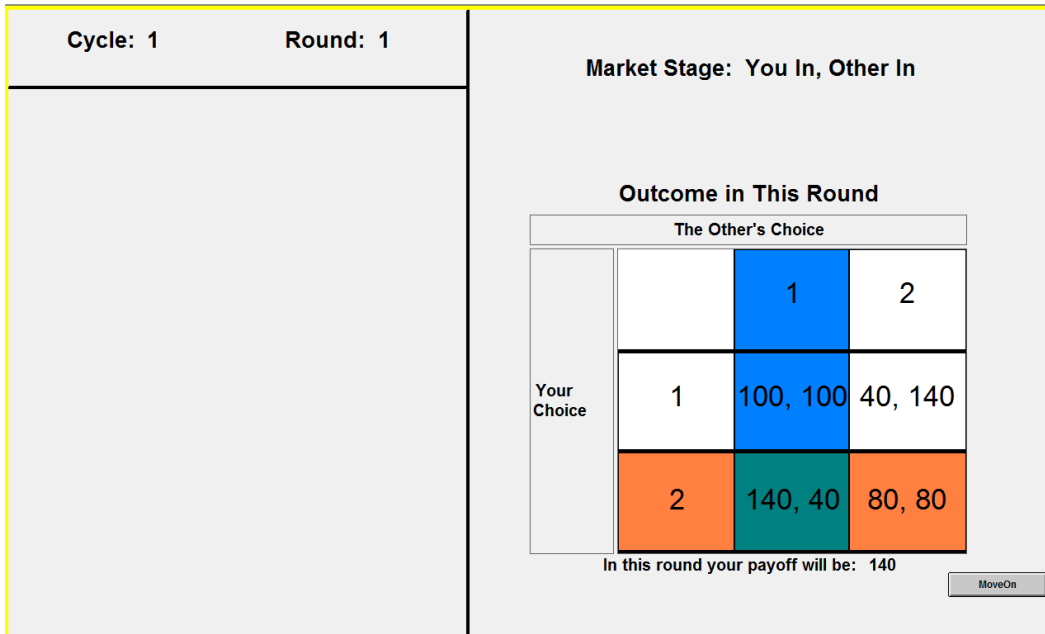


Figure 13: Example of Feedback when the subject selects 2 and the other selects 1.

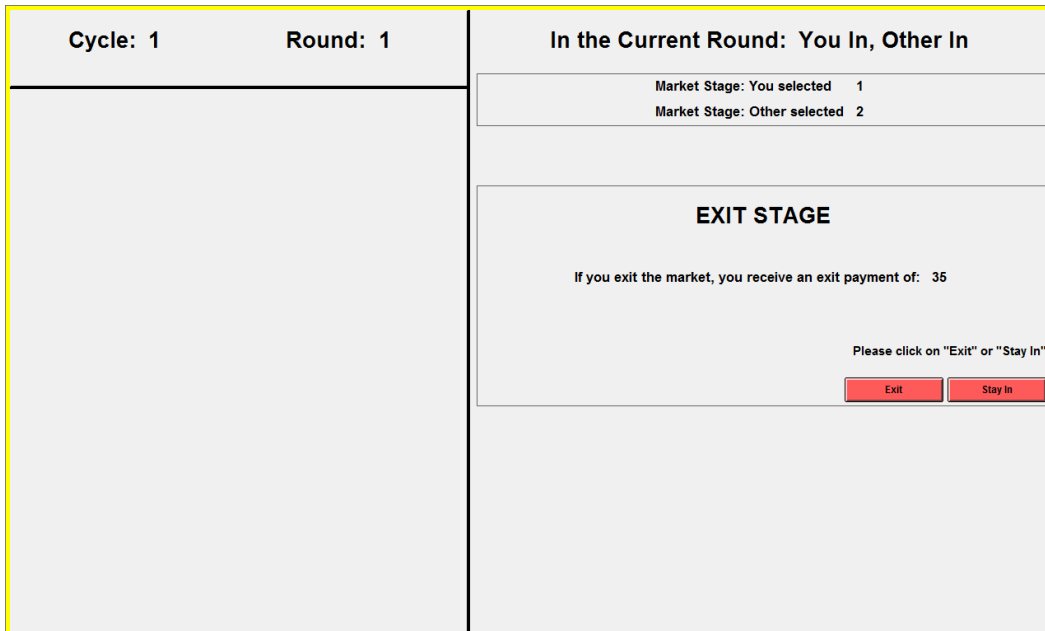


Figure 14: Example of an exit stage decision in cycle 1.

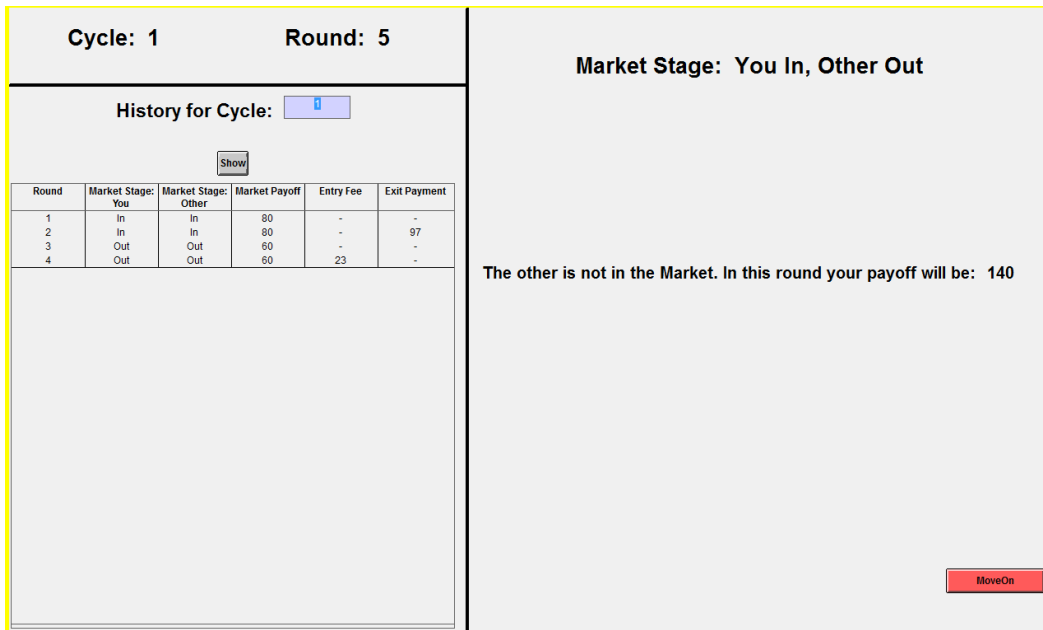


Figure 15: Example of quantity stage where there is No Quantity Choice.

Figure 16 presents an example of the exit decision for part 2 of the session. Subjects can select a threshold by clicking anywhere on the black line. Once they click on the horizontal black line a red vertical line appears with a red number indicating the choice. In the example the subject selects a threshold of 51. Once a choice is made the interface indicates with arrows the values of the scrap value for which the subject would exit or stay in the market. Subjects can change their choice by clicking anywhere else on the black line. They can also adjust their choice by clicking on the plus/minus buttons at the bottom. Each click in the plus (minus) button adds (subtracts) one unit to the current threshold. Once they click on 'submit' their choice is final.

Finally, Figure 17 shows an example of the feedback that subjects receive after they make an exit decision. First they are informed of the randomly selected scrap value (exit payment), then they are reminded of the threshold they finally submitted. Given these two values they are informed of the final decision.

Cycle: 1	Round: 1	In the Current Round: You In, Other In
		Market Stage: You selected 1 Market Stage: Other selected 2
		<p align="center"><b>EXIT STAGE</b></p> <p align="center">Make Your choice for the EXIT PAYMENT threshold</p> <p align="center">For an Exit Payment higher than 51 exit</p> <div style="text-align: center;"> </div> <p align="center">For an Exit Payment lower or equal than 51 stay in the market</p> <p align="center"> <input type="button" value="-"/> <input type="button" value="+"/> </p> <p align="center"> <input type="button" value="Submit"/> </p>

Figure 16: Example of an exit stage decision in cycles 2-16

Cycle: 1	Round: 1	In the Current Round: You In, Other In
		<p align="center">The Exit Payment this round is: 60</p> <p align="center">The Exit Threshold you selected was: 51</p> <p align="center">Because the Exit Payment is higher than your Exit Threshold you will Exit the Market and will be paid the Exit Payment.</p> <p align="right"> <input type="button" value="Move On"/> </p>

Figure 17: Feedback after exit stage decision in cycles 2-16