Supplier Capacity Decisions Under Retailer Competition and Delays: Theoretical and Experimental Results[†]

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ABSTRACT:

The bullwhip effect, the tendency for the variability of orders to increase as it moves upstream in a supply chain, is a frequent and costly source of problems in supply chains. An operational cause of such problems identified in the literature suggests that the amplification in orders take place when retailers compete for scarce supply. While this operational cause is intuitive and has been known for almost a century, there is little research quantifying the impact it causes in an upstream supplier. This paper presents a simple model describing the impact of retailer competition for scarce supply and describes an experiment to explore how a supplier reacts to inflated retailer demand. We provide experimental evidence that shows that a reinforcing loop created by retailer inflated orders leads to excessive capacity, backlog and costs for the supplier. The experiments also show that subjects perform poorly when compared to an optimal benchmark. In particular, longer times to build capacity lead to poorer subject performance relative to the optimal. In addition, more aggressive retailer competition for scarce resources also lead to poorer subject performance. Furthermore, our results suggest that when subjects face retailers that do not inflate orders by much (10% order inflation), the majority of the supplier costs are due to changes (investment or divestment) in capacity. Such high costs, reflecting that subjects change capacity too often, capture the inherent complexity of controling the capacity level. In constrast, when subjects face retailers that aggressively inflate orders (50% order inflation), the majority of the supplier costs are due to supplier backlog. Such high costs, reflecting that suppliers fail to lower their order backlog, capture the inherent complexity of managing the positive feedback loop of retailers' order inflation.

KEYWORDS: bullwhip effect, laboratory experiments, optimal control, behavioral operations, supply chain management, demand bubbles.

1. INTRODUCTION

One of the most frequent and costly source of problems in supply chains is known as the *bullwhip effect* (or *forrester effect*). This phenomenon captures the tendency for the variability of orders to increase as one moves upstream in a supply chain, with orders received by manufacturers being much more volatile than customer orders. The increased order variability leads to problems such as excessive capital investment, inventory gluts, inventory shortages, low capacity utilization and poor service (Armony and Plambeck 2005; Gonçalves 2003; Lee et al. 1997a; Sterman 2000). A number of recent examples highlight the supply chain impact of the *bullwhip effect*. A post-shortage demand surge for Hewlett-Packard's LaserJet printers lead to unnecessary capacity and excess inventory (Lee et al. 1997b). Increased orders and part shortages for pentium III processors in november 1999 motivated Intel to introduce a new Fab the following year (Foremski 1999), but large order cancellations and flat sales caused it to revised it soon after (Gaither 2001). Part shortages followed by a strong inventory built up and a drastic decrease in retailer orders caused Cisco Systems to post a US$ 2.7 billion inventory write-off and lay off 8500 people (Adelman 2001).

The *bullwhip effect* has been captured in the literature as early as 1924, when Mitchell described the case of retailers inflating their orders to manufacturers when competing with other retailers for scarce supply:

> [R]etailers find that there is a shortage of merchandise at their sources of supply.
> Manufacturers inform them that it is with regret that they are able to fill their orders
> only to the extent of 80 percent. … Next season, if [retailers] want 90 units of an article,
> they order 100, so as to be sure, each, of getting the 90 in the pro rata share delivered."
> (Mitchell 1924, p. 645)

The first formal model on supply chain instability dates back more than 50 years and coincides with the emergence of the field of system dynamics (Forrester 1958, 1961). Forrester highlighted that order fluctuations and amplifications in supply chains were caused by the structure of the system. Willard Fey converted this early supply chain work into a game, which subsequently evolved into the famous beer game. Using the Beer Game, Sterman (1989) econometrically explored the decision rules used by subjects playing the game and found that subjects behaved in a boundedly rational way, failing to account adequately for the supply line of unfilled orders.

Sterman's (1989) seminal paper motivated two important streams of research in order amplification and instability in supply chains. The first research stream explored through analytical models the operational causes that could lead to this amplification in demand variability. The operational causes included order batching, order gaming due to shortages, volume purchasing due to price discounts, and erroneous orders due to demand forecasting (Lee et al. 1997a) and demand forecasting techniques and order lead times (Chen et al. 2000). The second research stream explored using the Beer Distribution Game (BDG) ways in which the structure of the system could impact overall supply chain costs and order amplification. Some of the structural considerations included ordering and shipment delays (Kaminsky and Simchi-Levi 1998; Gupta, Steckel and Banerji 2001; Steckel, Gupta and Banerji 20004) and information sharing and Point-of-Sales (POS) data (Croson and Donohue 2003). Moreover, other experimental studies using the Beer Distribution Game (BDG) that controlled for the operational causes explored possible behavioral causes for the bullwhip effect (Croson and Donohue 2002 offer a review).

Because the BDG is a serial supply chain, it is not possible to explore the impact of order amplification as described by Mitchell (1924) and as captured in the rationing game proposed by Lee et al. (1997a). This paper proposes a formal model that captures the impact of the rationing game in an arborescent supply chain, where a single supplier sells to multiple retailers that compete for scarce resources. We first describe the model and solve it analytically to determine the optimal capacity trajectory that a supplier should follow to minimize retailers' overreaction to supply shortages and its associated costs. With a benchmark for the optimal supplier capacity investment, we then conduct a number of experiments where subjects play the role of a supplier investing in capacity to manage retailers' demand. Previous research (Gonçalves 2003) suggests that the problems described by Mitchell (1924) intensify under strong retailer competition for scarce resources, when the supplier faces capacity acquisition delays, and when customers have real time information about supply shortages. Analyzing subjects responses to different treatments (intensity of retailer overordering and length of supplier capacity acquisition delays), we explore subjects ability to manage costs incurred by retailers inflated ordering behavior.

Consistently with the theory, we find that subjects performance deteriorate when they face stronger retailer competition for scarce resources (intense order inflation) and when the supplier faces longer capacity acquisition delays. Subjects systematically deviate from the optimal benchmark. Moreover, econometrically analyzing subjects' decisions we gain insight on the decision rules used. We discuss the systematic biases that result from their decisions.

2. MODEL DESCRIPTION

The model captures the relationship of a single supplier selling a single product to multiple retailers. The emphasis of our analysis is on shedding light on the supplier problem of adjusting capacity to meet retailers' orders. In particular, we consider the case of a supplier with unique (non substitutable) products that allows her retain market share despite poor performance (i.e., long delivery delays and poor delivery reliability).
The supplier's backlog of orders (*B*) increases with retailers orders (R_d) and decreases with supplier shipments (*S*).

$$\dot{B} = R_d - S \quad (1)$$

Retailers' orders are modeled with an anchor and adjustment heuristic. Retailers anchor their orders on a forecast of final customer demand and adjust the anchor to maintain orders at a desired level with the supplier.

Hence, the anchor term captures retailers' intention to place sufficient orders to meet their customers' orders. The adjustment term closes the gap between a desired backlog of orders from retailers and actual backlog of retailers' orders. In addition, retailers close the gap between desired and actual backlog of orders within a specific adjustment time. For a supplier dealing with multiple retailers, total retailer demand is given by summing the orders of all retailers. We assume that each retailer adopts the same anchor and adjustment heuristic, however, each one may have different estimated values for the customer demand forecast, actual backlog, and desired backlog. Since our interest is on the supplier capacity adjustment decisions, our model captures the heuristic over all retailers with the total values for customer demand forecast (d), actual backlog or orders (B), desired backlog of orders (B^*), and adjustment time (τ_B). In addition, we consider that total retailers' orders are non-negative.

$$R_d = MAX\left(0, d + \frac{B^* - B}{\tau_B}\right) \tag{2}$$

Actual shipments are normally determined by the minimum of desired shipments and available capacity. Because we are interested in situations characterized by supply shortages, we model shipments as determined by available capacity (K).

$$S = K \tag{3}$$

The supplier's capacity (K) is given by a first-order exponential smooth of desired shipments, with a time constant given by the time to build capacity (τ_K). Desired shipments are given by the ratio of Backlog (B) and the Target Delivery Delay (τ_D). This formulation captures a naïve capacity planning process, where the supplier tries to maintain sufficient capacity to satisfy customer demand within a target delivery delay.

$$\dot{K} = \frac{B/\tau_D - K}{\tau_K} \tag{4}$$

Retailers' desired backlog of orders (B^*) is given by the product of the expected customer demand (i.e., the demand forecast, d) and the expected delivery delay to receive orders previously placed (ED). The expected delivery delays are determined by a function (f) of the actual delivery delays (AD), given by the ratio of the order backlog (B) to shipments (S).

$$B^* = d \cdot ED = d \cdot f(B/S) \tag{5}$$

The function (f) of the actual delivery delay captures retailers' delivery delay adjustment. That is, when faced with long delivery delays, retailers set their expected delivery delay (ED) above the actual delivery delay (AD) quoted by the supplier. Longer expected delivery delays (ED) than actual (AD) leads to higher desired backlog of orders (B^*) and higher retailers orders. That is, in anticipation of above normal delivery delays retailers inflate orders by setting the desired backlog of orders higher than necessary. Both the business press and academic literature provide evidence that retailers inflate orders when faced with supply shortages and the supplier proportionately allocates available capacity among retailers (Greek 2000, Lee et al. 1997a). For simplicity, we assume a retailer that sets the expected delivery delay proportionally to the actual delivery delay quoted by the supplier, with a linear function of slope α).

$$f(x) = \alpha \cdot x \text{, where } \alpha \geq 1 \tag{6}$$

While retailers can often cancel orders, we capture cancellations implicitly through the natural adjustment of the desired retailer order backlog.

Our model emphasizing a supplier selling to multiple retailers, maintains two state variables, keeping track of the supplier order backlog (B) and its capacity (K). The entire model is captured in a second order system of first order non-linear differential equations shown in equations (7-8) and represented graphically in figure 1.

$$\dot{B} = MAX(0, d + \frac{d \cdot \alpha \cdot B / K - B}{\tau_B}) - K \tag{7}$$

$$\dot{K} = \frac{B/\tau_D - K}{\tau_K} \tag{8}$$

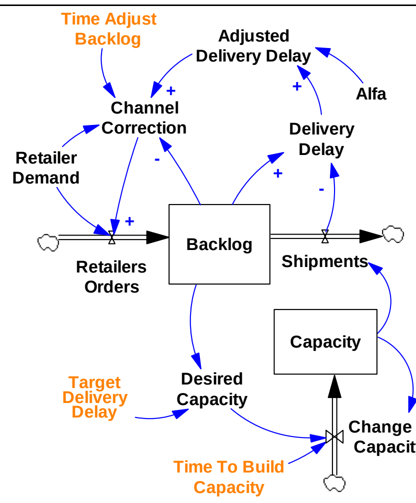


Figure 1. System dynamics diagram for supplier-retailer system.

2.1. Model Behavior

The system of first order non-linear differential equations cannot be solved in closed form, so we simulate the model for 20 simulated weeks. Initially, the model is set in dynamic equilibrium, such that backlog and capacity stay at their normal values. We then introduce a permanent 10% increase in final customer demand (d) at the beginning of the simulation to gain intuition about model behavior.

Figure 2 shows backlog, capacity and change in capacity for the supplier. Due to the increase in final customer demand, retailers' orders exceed supplier capacity causing an increase in backlog. As backlog increases, retailers experience longer delivery delays. Because the supplier cannot meet all retailers' orders with the normal delivery delay, retailers inflate orders by adjusting delivery delays. Higher retailers'orders further increase backlog. The supplier invests in capacity to meet the increase in retailers' orders, but it takes time before the investment in capacity allows the supplier to meet demand. Initially, capacity investment takes place at an increasing rate. It peaks at about 5 weeks, and then capacity continues to expand at a decreasing rate.

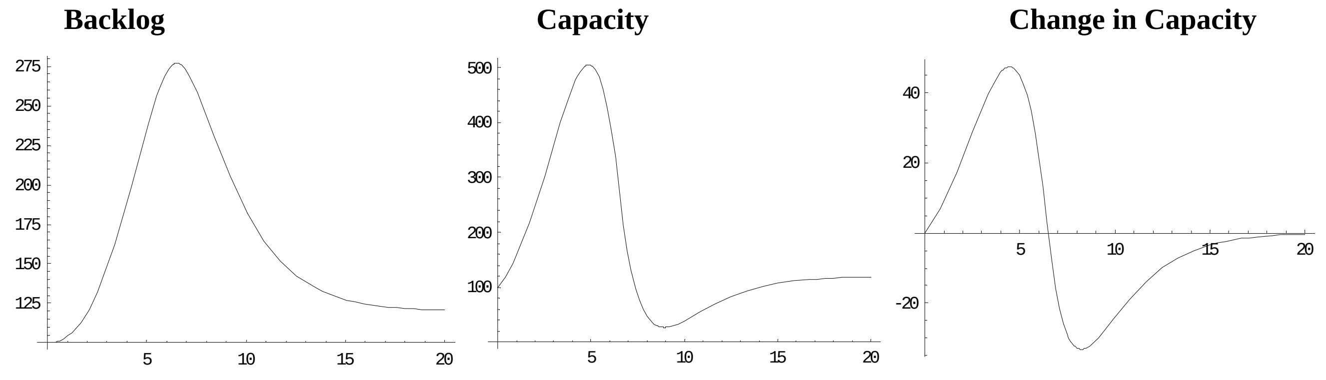


Figure 2. Supplier's (a) backlog, (b) capacity, (c) change in capacity (w/10% increase in customer orders).

When capacity increases high enough such that outgoing shipments equate incoming orders, backlog reaches a maximum. At this point, desired capacity also peaks and capacity investment turns to divestment. As the supplier tries to meet inflated orders from retailers, it dramatically overinvests in capacity. The boom-and-bust in supplier's capacity and backlog represent an important aspect of this system behavior. While final customer demand increases by 10% for one year, supplier backlog and capacity increase significantly more (respectively 200% and 400% given the specific values in our simulation) relative to final equilibrium levels.

3. OPTIMAL CONTROL

The system determined by equations (7-8) is simple enough to almost be solved using optimal control. Unfortunately, it involves a nonlinearity associated with actual delivery delays (*AD*), given by the ratio of the two states: order backlog (*B*) to capacity (*K*). Taking the first-order Taylor series approximation of the ratio of the two states (*B*/*K*) we can linearize the system and solve it. Naturally, the linearized system approximates the nonlinear formulation for delivery delay. Taking the first-order Taylor series approximation we obtain:

$$DD = \frac{B}{K} = \frac{B_0}{K_0} + (B - B_0)\frac{1}{K}\bigg|_{B_0,K_0} + (K - K_0)\frac{B}{K^2}\bigg|_{B_0,K_0} =$$

$$= \frac{B_0}{K_0} + (B - B_0)\frac{1}{K_0} + (K - K_0)\frac{B_0}{K_0^2} \qquad (9)$$

and since in equilibrium we have that $K_0 = B_0 / \tau_D$, the linearized form for delivery delays is given by:

$$DD = \tau_D \left(1 + \left(\frac{B/\tau_D - K}{K_0} \right) \right) \qquad (10)$$

Also, because we assume that the supplier faces supply shortages (see the motivation for equation 3), we must impose an additional constraint to equation (10), guaranteeing that the supplier is capacity constrained, such that capacity (*K*) is smaller than the desired shipments (B/τ_D).

$$DD = \tau_D \left(1 + MAX\left(0, \frac{B/\tau_D - K}{K_0} \right) \right) \tag{11}$$

Rewriting the system of equations, we see that the new system includes a sharp nonlinearity, but it is piece-wise linear and can be solved using optimal control. Also, we set the change in supplier capacity ($\dot{K}$) as our control policy, we obtain the following system:

$$\dot{B} = d + \frac{d\alpha\tau_D}{\tau_B} \left(1 + MAX\left(0, \frac{B/\tau_D - K}{K_0} \right) \right) - \frac{B}{\tau_B} - K \tag{12}$$

$$\dot{K} = u \tag{13}$$

Next, we establish a cost function that allows us to find the optimal capacity investment trajectory for the supplier. In particular, the total accumulated cost (*TC*) is given by three components: the capacity cost, the backlog cost and the cost to change capacity. The capacity cost (*K*) captures the cost associated with maintaining available production capacity. The backlog cost (*B*) captures the cost of carrying unmet retailer orders. The change in capacity cost (*u*) captures the cost associated with implementing investment and divestment decisions. All costs are linear quadratic, reflecting the fact that larger deviations from the equilibrium points are heavily penalized.

$$TC = \int_t \left(\varepsilon K_t^2 + \phi B_t^2 + \delta u_t^2 \right) \tag{14}$$

Using optimal control to minimize the total accumulated cost for each of the two piece-wise linear systems, provides the optimal capacity investment trajectory for the supplier. The dashed lines (Figure 3) show the optimal change in capacity compared with the simulated performance using the change in capacity heuristic (equation 8).

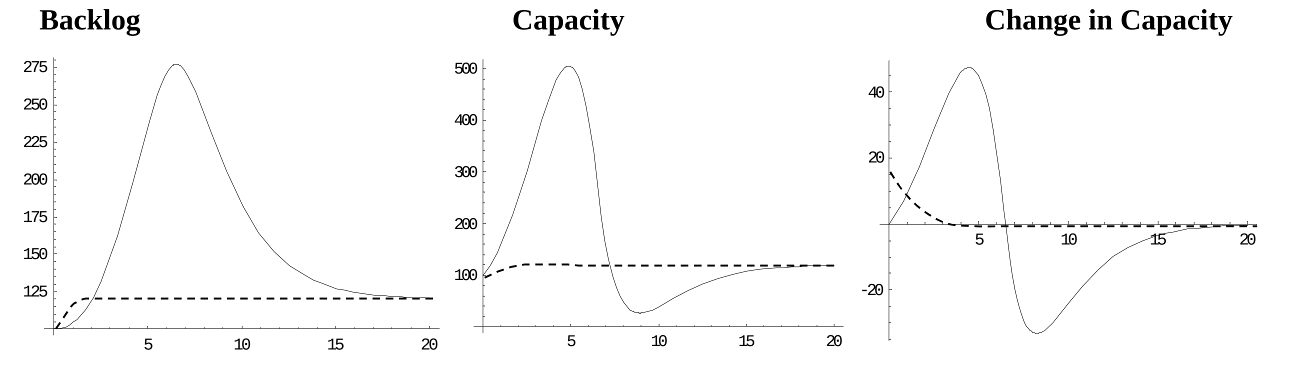


Figure 3. Optimal Supplier's (a) backlog, (b) capacity, (c) change in capacity (10% increase in orders).

4. THE EXPERIMENT

We implement the model described above in a "management flight simulator" (Senge and Sterman 1992). Subjects play the role of a supplier responding to retailers' demand. Following an automated decision rule, retailers' orders, placed by the computer, are inflated to compensate by shortages in supply. The supplier is informed that a supply shortage exists and that retailers are likely to inflate orders to try to get the supply they need. Subjects must decide to -adjust production capacity, investing (or divesting) in production capacity each week through 40 simulated weeks.

The experiment starts in dynamic equilibrium. That is, initially the supplier has sufficient production capacity to meet total retailer demand according to the target delivery delay. At time *t*=3, however, the supplier faces a sudden increase in retailer orders. In particular, subjects are instructed that:

> Initially, retailers order 100 units per week, which allows you to maintain a target delivery delay of 10 weeks. Recently, novel applications of your products generated an increase in demand. You estimate that the increase in demand will be permanent and in the order of 20 additional units per week. Since you were not aware of these new applications, the increase in demand took you by surprise, so you are no longer able to meet total retailer demand. With insufficient capacity to meet total demand, your delivery delays increase. You know that retailers respond to this increased delivery delay with orders that are inflated.

Subjects must make capacity investment decisions each week (0 investments is also a feasible decision). Each player' goal is to minimize the total accumulated cost (*TC*), equation (1), during the 40 simulated weeks. There are three cost components in the total accumulated cost (*TC*): (1) capacity cost, (2) backlog cost, and (3) change in capacity cost. The time horizon of 40 weeks is long enough to allow subjects to control the system after a one time increase in demand at time (*t=2*).

$$TC = \sum_{t=1}^{T}\left(\varepsilon K_t^2 + \phi B_t^2 + \delta u_t^2\right) \qquad (15)$$

where, $\phi = 2.10^{-5}$, $\varepsilon = 2.10^{-3}$, and δ=2

4.1. Experimental Treatments

Our experiment explores two characteristics – retailer competition for scarce supply and supplier capacity acquisition delays – identified in previous research (Gonçalves 2003) that are capable of influencing retailer order inflation. We use a full experimental design, with four experimental treatments – with two different delays to change capacity (Short =1; Long =3) and two levels of retailer order aggressiveness (10% increase in orders, α=1.1; and 50% increase in orders, α=1.5%). Table 1 specifies all treatments conducted in the experiment.

Table 1. Experimental treatments.

	Retailer Order Aggressiveness

		(dmnl)	
		1.1	**1.5**
Capacity Investment Delay (weeks)	**1**	***T1*** (N=19)	***T3*** (N=19)
	3	***T2*** (N=19)	***T4*** (N=18)

4.2. Protocol

We follow standard experimental economics protocol (see Friedman & Sunder, 1994 and Friedman & Cassar, 2004). Subjects were recruited from the same population during autumn 2009, by an open call to fourth and fifth year Industrial and Management Engineering students at the National University of Colombia, Medellín, Colombia. The subjects did not have previous experience in any related experiment. Participants were told they would earn a show-up fee of Col$10.000 (aproximately US$5) and a variable amount contingent on their performance, between Col$0 and Col$30.000 (US$0 - US$15). The experiment ran for around 1 hour and students were informed about the duration of the experiment, impling that the payoff was larger than their opportunity cost in Colombia. The students were also given a set of instructions describing the production system, the decisions and the goals of the game (as it is shown in the instruction in Appendix 2).

We ran the experiment with 80 subjects, with 20 subjects per treatment. Upon arrival, subjects were seated behind computers and a treatment was assigned randomly. Instructions (see Appendix 2) were distributed and they were read aloud by the experimenter. Participants were allowed to ask questions and test out the computer interface. All the experiment parameters were common knowledge to all participants. After analysis of subjects' decisions, we removed five of them from the intial sample. The excluded subjects' behavior deviated markedly from those of other subjects. In particular, three excluded subjects made few (or a single) capacity decisions of a dramatic magnitude (e.g., capacity investment of 50000 units/week, 500 times above initial) and two performed large and close in time investment and divestment decisions (e.g., investing almost 13,000 units/week then divesting capacity by more than 3,000 units/week). The removal of these subjects does not change the overall results obtained, but they prevent our statistical analysis to be swayed by these extreme cases. In the presentation of our results, we consider the 75 remaining subjects, about 19 per treatment (as shown in table 1).

The experiment was run in the computer simulation software *Powersim Constructor 2.51*®. The software ran automatically and kept record of all variables, including subjects' decisions. Subjects were also asked to write their decisions in a sheet of paper, which serve as a physical backup of the date. The software interfaces are presented in Appendix 1 (in Spanish) and is available upon request.

5. RESULTS

5. 1. Subjects' Cost Performance

Subjects in our experiments perform far from optimal. Table 2 presents total cumulative, average, and optimal costs for subjects in all treatments. The under-performance is dramatic in all treatments. The lowest total cost achieved by a subject was 48% higher than the optimal value for that treatment (subject P19 in treatment T3). Best performances (i.e., minimum costs achieved) in other treatments were also significantly above optimal costs: 69% above optimal in treatment 1 (T1), 81% above optimal in treatment 2 (T2), and 145% above optimal in treatment 4 (T4). Subjects performance vary significantly across and within treatments, with average costs ranging from 12 to over 900 times higher than optimal performance (average costs ranged from $2.6 x10^4 (T1) to 4.5 x10^6 (T3) and minimum costs ranging from $3.5 x10^3 (T1) to 2.2 x10^4 (T4)).

Table 2. Total cumulative, average, and optimal costs across treatment for the experiment.

Subject	T1	T2	T3	T4
P1	$ 4,550	$ 41,585	$ 64,956	$ 163,333
P2	$ 3,506	$ 4,591	$ 35,274	$ 2,207,045
P3	$ 14,098	$ 7,029	$ 15,057	$ 179,053
P4	$ 17,179	$ 19,257	$ 8,021	$ 35,456
P5	$ 13,192	$ 8,677	$ 35,717	$ 22,345,303
P6	$ 4,984	$ 17,100	$ 21,766	$ 25,121
P7	$ 74,924	$ 86,995	$ 4,101,140	$ 743,389
P8	$ 114,975	$ 30,642	$ 26,099	$ 42,207
P9	$ 44,051	$ 80,648	$ 28,528,807	$ 31,206
P10	$ 14,460	$ 7,575	$ 12,078,599	$ 37,898
P11	$ 12,833	$ 5,324	$ 14,859	$ 368,293
P12	$ 11,619	$ 130,616	$ 14,530,124	$ 22,265
P13	$ 10,747	$ 12,005	$ 8,654	$ 737,533
P14	$ 6,460	$ 1,030,244	$ 9,428,516	$ 2,265,392
P15	$ 59,122	$ 29,989	$ 120,432	$ 2,388,688
P16	$ 17,889	$ 27,376	$ 435,705	$ 101,572
P17	$ 9,226	$ 6,270	$ 16,619,950	$ 85,443
P18	$ 24,839	$ 11,748	$ 141,681	$ 387,342
P19	$ 28,136	$ 39,394	$ 7,365	
Average	*$ 25,621* (12)	*$ 84,056* (33)	*$ 4,538,038* (914)	*$ 1,787,030* (197)
Min	*$ 3,506* (1.69)	*$ 4,591* (1.81)	*$ 7,365* (1.48)	*$ 22,265* (2.45)
Optimal	*$ 2,069*	*$ 2,543*	*$ 4,967*	*$ 9,074*

Note: Numbers in parenthes for average and means show the ratio between the average (and minimum) values and the optimal ones.

Table 3 presents average cumulative costs for each cost component: change in capacity cost (*KC*), capacity cost (*K*), and backlog cost (*B*). The table also presents the percentage of the total costs (actual subject costs and optimal costs) associated with each cost component. The results highlight the difference in component costs for all four treatments. Subjects in treatments T1 and T2 incur the largest fraction of costs through changes in capacity (*KC*), respectively 79% and 92% of total costs. In contrast, the optimal cost fraction for changes in capacity (*KC*) in treatments T1 and T2 are respectively 20% and 11%. The remaining percentage of optimal costs would be well balanced between capacity cost (*K*) and backlog cost (*B*). In treatments T3 and T4, however, subjects incur the majority of costs by maintaining a high backlog of orders (*B*), respectively 94% and 70% of total costs. In contrast, the optimal cost fraction for backlog (*B*) in treatments T3 and T4 are respectively 19% and 26%.

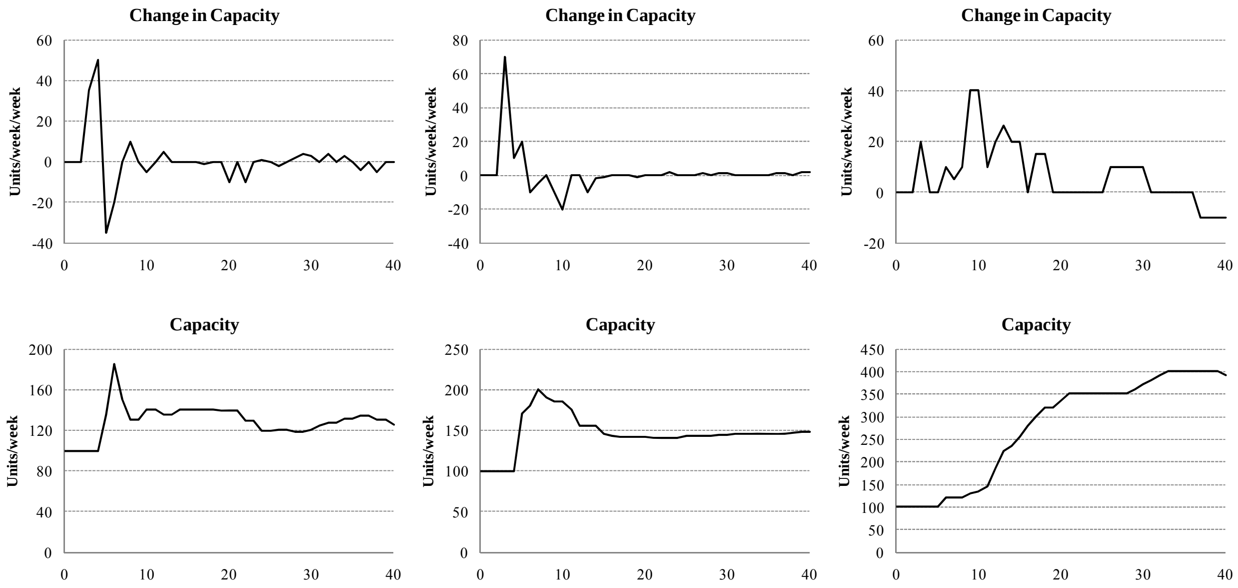
The high fraction of change in capacity (*KC*) cost in treatments T1 and T2 and of backlog (*B*) cost in treatments T3 and T4 provide clues about the sources of underperformance. The inherent complexity of the task – mild order inflation (10%) under short (T1 = 1 week) or moderate (T2 = 3 weeks) capacity delays – cause subjects to implement too many costly changes in capacity. Hence, costs associated with changes in capacity in treatments T1 and T2 account for the majority of total costs. While we have not tested the reaction of the subjects without order inflation (0%) and without a delay (immediate change in capacity) it would provide a useful benchmark to compare the current results of our simplest treatments. In treatments T3 and T4, however, the inherent complexity of managing the positive feedback loop account for the majority of costs. Treatments T3 and T4 capture subjects reaction to strong retailer order inflation (50%) under short (T3 = 1 week) or moderate (T4 = 3 weeks) capacity delays. As subjects struggle to control backlog early, the positive feedback loop takes off with retailers generating sizable inflated orders and destabilizing the system. Hence, costs associated with high backlog in treatments T3 and T4 account for the majority of total costs.

Table 3. Average cost detailed by KC, K, and B, percentage of the cost for actual and optimal total cost.

		Change Capacity *KC*	**Capacity *K***	**Backlog *B***
T1	Average	20136	3460	2025
	% Actual	79%	14%	8%
	% Optimal	20%	41%	39%
T2	Average	77358	5099	1599
	% Actual	92%	6%	2%
	% Optimal	11%	42%	46%
T3	Average	273979	8325	4255735
	% Actual	6%	0%	94%
	% Optimal	55%	27%	19%
T4	Average	458719	78393	1249918
	% Actual	26%	4%	70%
	% Optimal	43%	32%	26%

5. 2. Subjects' Capacity Investment Behavior

Subjects are informed that due to novel applications of their products final customer orders will increase by 20% and that retailers should inflate orders to compensate for scarce supply. Subjects are also informed about the (short or moderate) delay required to add new capacity. Figure 4 presents typical capacity investment decisions and subsequent capacity for three randomly selected subjects in treatments T1, T3 and T4. The results suggest that subjects' capacity investment decisions are far from optimal. Subjects in different treatments make similar capacity investment decisions. Subjects initially over-invest in capacity, investing too much for too long. They then proceed to divest any perceived excess in capacity. This over-investment and divestment cycle is atenuated over time but can take place in subsequent weeks. The final result across subjects is overinvestment in capacity.



T1-P_3 T3-P_3 T4-P_7

Figure 4. Typical experimental results (P_j indicates the subject number with $j = 1,\ldots,20$).

To identify systematic differences across treatments, we compute the average change in capacity and average capacity for all players in each treatment (see figure 5). The average capacity investment decisions lead to capacity results that are far from optimal. All subjects in all treatments over invest in capacity. Despite the similarities among subjects' decisions, there are also marked differences across treatments. The peak in subjects' capacity inventment decision tends to occur earlier in treatments with shorter delays. Capacity investment decisions are more variable and take longer to settle in treatments with higher retailer order aggressiveness. The retailer order aggressiveness variable establishes the gain for the reinforcing loop of retailer order inflation. Treatments T1 and T2 have low aggressiveness (10% increase in retailers' orders); treatments T3 and T4 have high aggressiveness (50% increase in retailers' orders). Consistently, treatments T3 and T4 with stronger aggressiveness (higher loop gain) lead to larger orders, higher backlog and force subjects to make larger investments in capacity compared with those for treatments T1 and T2. Consider for instance treatments T1 and T3, average capacities in both treatments remain relatively close until week 14, then they slowly deviate from each other, with subjects in treatment T3 over investing in capacity beyond subjects in treatment T1. The larger retailer order inflation in treatment T3 causes subjects to invest more in capacity to manage the more aggressive bubble in demand.

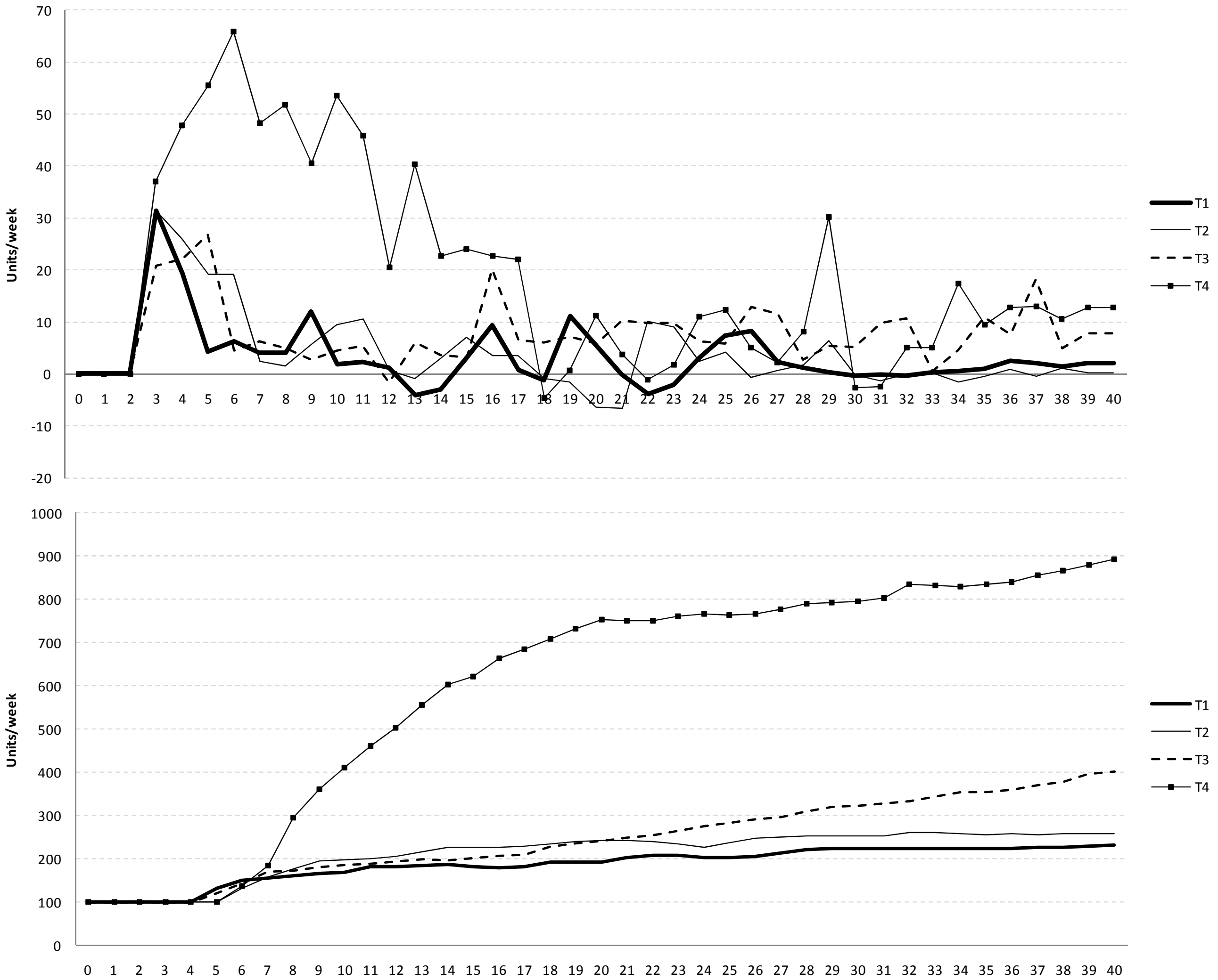


Figure 5. Average capacity investments (upper panel) and average capacity (bottom panel) over time for all treatments.

In general, subjects' decisions have lower instability in simpler treatments (shorter delays and low gain for the reinforcing loop) and higher variability in more complex treatments. In particular, capacity investment decisions in dynamically simple tasks (e.g. treatment T1) lead to final capacity values that are closest to optimal; capacity investment decisions in dynamically complex tasks (e.g. treatment T4) lead to final capacity values that are farthest from optimal.

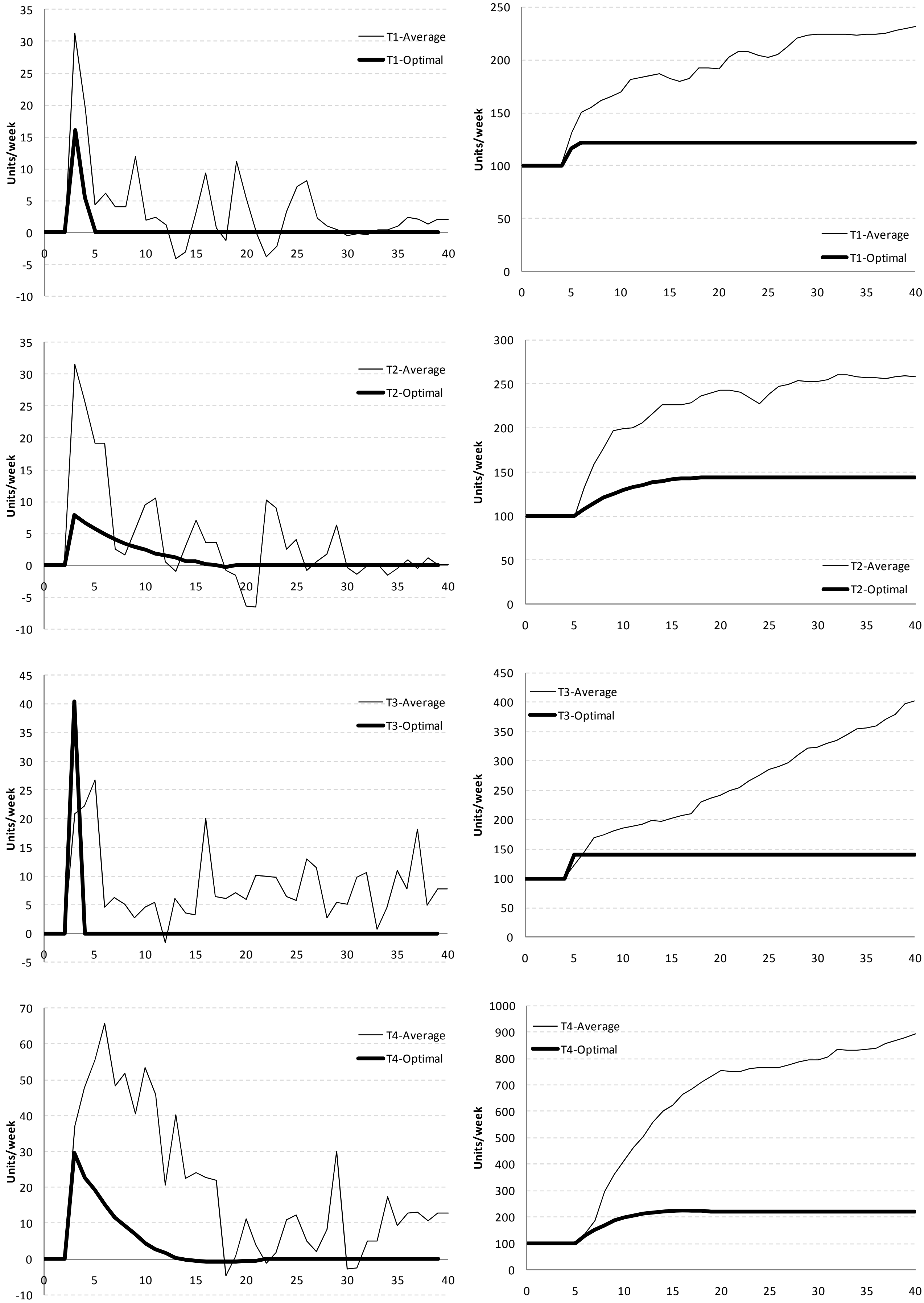


Figure 6. Average capacity development across treatments.

Figure 6 presents actual and optimal capacity investment decisions and subsequent capacity over the time horizon of the experiment across the four treatments. The optimal capacity investment decision in all treatments is simple, following an exponential decay until it stabilizes at zero. Subjects' capacity investment decisions deviate significantly from optimal. In particular, final capacity for subjects dramatically exceeds the optimal capacity in all treatments. The ratio between subjects' final capacity and optimal capacity shows that subjects overinvest in capacity by a factor of 1.7 for T1 and T2; 2.8 for T3 and then to 4.4 for T4.

6. MODELING DECISION RULES

To get insight into the nature of the subjects' decisions, we consider the heuristics that they may use. A possible heuristic that the supplier might use is to maintain sufficient capacity to satisfy customer demand within a target delivery delay. With this decision rule, the supplier change in capacity ($\dot{K}$) would be given by the gap between actual capacity (K) and desired shipments (B/τ_D), adjusted within the time required to build capacity (τ_K):

$$\dot{K} = \frac{B/\tau_D - K}{\tau_K} \tag{16}$$

Econometrically, such decision rule would be determined by the following model:

$$\dot{K}_{t,j} = \beta_{0j} + \beta_{1j} B_t + \beta_{2j} K_t + \varepsilon_{t,j} \tag{17}$$

where β_{ij} represent the coefficients and $\varepsilon_{t,j}$ is the error term. According to the decision rule above, we expect β_{0j} not to be significantly different than zero, β_{1j} to be positive and β_{2j} to be negative, where estimates of coefficients β_{1j} and β_{2j} would be given by $1/\tau_K \tau_D$ and be given by $-1/\tau_K$ respectively.

Alternatively, the supplier might use an heuristic that adjusts capacity to a demand forecast. Assuming a naïve demand forecast obtained by actual retailers' orders (R_d), where retailers' orders are characterized by the first-order Taylor Series approximation of the non-linear orders:

$$R_d = d + \frac{d\alpha\tau_D}{\tau_B}\left(1 + MAX\left(0, \frac{B/\tau_D - K}{K_0}\right)\right) - \frac{B}{\tau_B} \tag{18}$$

With this decision rule, the supplier change in capacity ($\dot{K}$) would be given by the gap between actual capacity (K) and the demand forecast, adjusted within the time required to build capacity (τ_K):

$$\dot{K} = \frac{\left(d + \frac{d\alpha\tau_D}{\tau_B}\left(1 + MAX\left(0, \frac{B/\tau_D - K}{K_0}\right)\right) - \frac{B}{\tau_B}\right) - K}{\tau_K} \tag{18}$$

Isolating individual terms, we would arrive at the following equation:

$$\dot{K} = \left(\frac{d}{\tau_K} + \frac{d\alpha\tau_D}{\tau_K\tau_B}\right) + \left(\frac{d\alpha}{K_0\tau_K\tau_B} - \frac{1}{\tau_K\tau_B}\right)B - \left(\frac{d\alpha\tau_D}{K_0\tau_K\tau_B} - \frac{1}{\tau_K}\right)K \tag{19}$$

Again, we could test such decision rule using the following econometric model:

$$\dot{K}_{t,j} = \beta_{0j} + \beta_{1j}B_t + \beta_{2j}K_t + \varepsilon_{t,j} \quad (20)$$

where again β_{ij} represent the coefficients and $\varepsilon_{t,j}$ is the error term. According to the decision rule above,

Estimates of the coefficients would be given by the above decision rule above, with $\beta_{0j} \approx \left(\frac{d}{\tau_K} + \frac{d\alpha\tau_D}{\tau_K\tau_B} \right)$,

$\beta_{1j} \approx \left(\frac{d\alpha}{K_0\tau_K\tau_B} - \frac{1}{\tau_K\tau_B} \right)$, and $\beta_{2j} \approx -\left(\frac{d\alpha\tau_D}{K_0\tau_K\tau_B} - \frac{1}{\tau_K} \right)$. This decision rule would lead to a coefficient of

β_{0j} significantly different than zero, β_{1j} to be positive and again β_{2j} to be negative.

Table 4. Coefficient estimates for two possible heuristics.
Parameter values: $d = 100$, K_0=100, τ_D=10, τ_K=6, τ_B=4.

Heuristic		β_0	β_1	β_2
Desired shipments	α= 1.1	0	.042	-.167
	α= 1.5	0	.042	-.167
Demand forecast	α= 1.1	62.5	.0042	-.292
	α= 1.5	79.2	.0208	-.458

The model is identified for each treatment *j* (*j=T1, ... , T4*), the time *t* goes from *t*=3 to 40. We use OLS for the estimation of the model in equation 12. Table 4 shows the estimations for β_{ij}, the average values for the coefficients for all data and for significant values. The table also shows the r^2 values for all regressions. A priori, we expect β_{1j} to be positive and β_{2j} to be negative for all treatments *j*. This result is intuitive. Large values of backlog and small values of capacity indicate the need to invest in more capacity; hence positive β_{1j} and negative β_{2j} respectively. Still, the expected coefficients for backlog are small.

The coefficient β_{1j} is consistent with our expectations, with negative values and significant values in the large majority. We found significant values for 11, 13, 11, and 15 significant values in treatments T1, T2, T3, and T4 respectively, which means the 67% of the whole sample. Nevertheless, estimations were not as expected for β_{1j}, since only 28% of the estimations are significant. The results for β_{1j} with respect to the expected sign is mixed, we observe 3 positive out of 6 significant values for T1, 1 out of 5 for T2, half of them for T3 and 5 out of 6 for T4. The constant is significant for half of the sample. Finally, we also observe more than 40% of r^2 values are larger than 0.40. The average values for significant estimations β_{2j} is reduced with the complexity of the treatment, this is that the largest value is -0.47 for T1, while the lowest value is -0.07 for T4. This average values also show consistency with negative values for β_{2j}, but mixed results for β_{1j}. β_{1j} is opposite to expectation for all treatments except for T3, but still all values are close to zero. R-squares show that regressions on average are between 0.32 and 0.45.

Table 5. Coefficient estimates of decision rule for each individual for all treatments.

Subject	T1				T2			
	$\beta_{2,1}$	$\beta_{1,1}$	$\beta_{0,1}$	r^2	$\beta_{2,2}$	$\beta_{1,2}$	$\beta_{0,2}$	r^2
1	-0.58†	0.22†	-143.85†	0.88	-0.42†	-0.04	129.63†	0.36
2	-0.26†	0.00	27.75†	0.45	-0.19†	-0.01	40.75†	0.22
3	-0.63†	-0.04	124.47†	0.45	-0.25†	0.00	45.54	0.45
4	-0.60†	-0.06†	179.92†	0.89	-0.44†	-0.07	143.48†	0.29
5	0.01	0.02	-15.66	0.25	-0.21†	0.00	27.14†	0.18
6	-0.07	0.00	12.29	0.12	-0.23	0.00	21.64	0.07
7	-0.47†	-0.07	182.53	0.28	-0.05	0.00	35.03	0.11
8	-0.07	0.01	9.31	0.12	-0.33†	-0.03†	119.28†	0.80
9	-0.29†	-0.01†	113.38†	0.89	-0.38†	-0.03	89.30	0.33
10	-0.88†	-0.30†	457.59†	0.74	-0.16†	-0.01	40.34†	0.62
11	-0.65†	-0.10†	210.85†	0.56	-0.22†	-0.03†	64.91†	0.30
12	0.03	0.01	-7.95	0.13	-0.01	0.01	27.60	0.21
13	-0.37†	-0.01	69.07	0.45	0.03	0.01	-11.33	0.38
14	-0.30†	0.05†	-6.01	0.90	-0.23†	0.01	68.48†	0.25
15	-0.07	0.08	-51.88	0.42	-0.53†	-0.08†	175.80†	0.37
16	-0.06	0.00	7.76	0.07	-0.06	0.02	5.97	0.52
17	0.01	-0.01	11.30	0.07	-0.22	-0.01	37.08	0.11
18	-0.06	0.01†	0.45	0.11	-0.46†	-0.10†	181.32†	0.38
19	-0.19†	-0.01	70.70†	0.77	-0.07†	0.01†	26.07†	0.48
Average-all	-0.29	-0.01	65.90	0.45	-0.23	-0.02	66.74	0.34
Average-sign	-0.47	-0.03	130.10		-0.30	-0.04	92.47	

Subject	T3				T4			
	$\beta_{2,3}$	$\beta_{1,3}$	$\beta_{0,3}$	r^2	$\beta_{2,4}$	$\beta_{1,4}$	$\beta_{0,4}$	r^2
1	-0.03†	0.005	6.57	0.47	-0.06†	0.0002	22.15†	0.17
2	-0.68†	-0.080†	219.88†	0.55	-0.02	0.0010	162.92†	0.17
3	-0.36†	0.001	54.62	0.32	-0.11†	0.0005	74.83†	0.25
4	-0.36†	0.010†	51.86†	0.88	0.02†	0.0054	2.86	0.77
5	-0.09	0.002	19.21	0.12	-0.10†	0.0000	18.19†	0.23
6	-0.14†	0.025†	14.71	0.62	-0.03†	0.0038†	10.80	0.46
7	0.07	0.000	11.65	0.15	0.36†	0.0637	-103.19	0.48
8	0.64	0.092	-38.04	0.21	-0.24†	0.4520	49.85†	0.25
9	0.19	0.000	-20.31	0.02	-0.29†	-0.0029	66.61†	0.38
10	-0.07	0.000	13.75†	0.09	-0.03†	0.0036†	10.84†	0.54
11	-0.25†	-0.030	90.10†	0.25	-0.13†	0.0083†	106.20†	0.28
12	-0.06	0.000	15.60	0.71	-0.02	0.0015	10.98	0.14
13	-0.48†	-0.037	117.62	0.53	-0.12†	0.0000	141.15†	0.25
14	-0.08†	0.000	14.27†	0.20	-0.04†	0.0004	68.59†	0.31
15	-0.01	0.000	10.46	0.02	-0.05†	0.0019†	253.62†	0.55
16	-0.18†	-0.003	134.25†	0.25	-0.01†	0.0198	7.70	0.09
17	0.14†	0.000†	-10.44	0.29	0.00	-0.0443†	0.00	0.00
18	0.01	0.004	-5.09	0.59	-0.14†	0.0166†	97.46†	0.42
19	-0.23†	0.012†	21.64†	0.65				
Average-all	-0.10	0.00	38.02	0.37	-0.06	0.03	55.64	0.32
Average-sign	-0.24	0.001	23.45		-0.07	-0.002	89.37	

† Significant at 5%.

We structured the data from the experiments as a panel, i.e. we build a data set with cross-sectional time-series. With individual players the cross-sectional unit (*i*) and week of decision time index (*t*). This panel data structure allows making estimations across individuals and echelons; thus, it increases the efficiency of the estimations and improves the representativeness of the decision rule compared with the previous estimations at the individual level of Table 5. We assume the occurrence of random effects across individual (Greene, 1997) for each treatment. It is supported in the fact that there is no expectation that the estimation of the constant β_{0j} would capture individual differences, and the subjects are a limited sample of the population. Thus, individual analysis estimates multiple coefficients, panel data helps to explain overall behavior. The panel data were estimated using Stata 11.1, which has implemented the random-effects cross-sectional time series with GLS (Stata, 2003).

Table 6. Coefficient estimates of decision rule for treatment as panel data.

Regressor	*Treatment T1*	*Treatment T2*	*Treatment T3*	*Treatment T4*
β_0 Constant	10.596 ***	13.591 ***	3.3602 *	33.052 ***
	(2.0547)	(3.0744)	(2.0093)	(4.9384)
β_1 Backlog (B_t)	-0.00015	-0.00139	0.00002 **	8.40×10^{-6}
	(0.00786)	(0.00096)	(0.00001)	(0.00005)
β_2 Capacity (K_t)	-0.00015 ***	-0.03681 ***	0.01698 *	-0.02005 ***
	(0.00061)	(0.01013)	(0.00576)	(0.00409)
Wald χ^2	21.37 ***	16.53 ***	13.76 ***	26.61 ***
R^2				
Within	0.17	0.14	0.01	0.17
Between	0.55	0.92	0.69	0.71
Overall	0.03	0.02	0.04	0.01
ρ	0	0	0	0.056
N observations	722	722	722	684

Standard error (SE) in parentheses: * significant at 10%; ** significant at 5%; *** significant at 1%

Estimations of panel data are shown in Table 6. The table also shows the Wald test and its significance and R2 (within, between, and overall). On the one hand, the coefficients β_{1j} are, unexpected, not significant for all treatments j except for T3, which coefficient $\beta_{1,3}$ is positive but lower that the expected value (see Table 4). On the other hand, the coefficients $\beta_{2,j}$ are both significant at 1% level and, as expected, positive for all j. The constant β_{0j} is positive and highly significant for all treatment j. Despite the fact that the overall r2 is very low for within and overall, it shows very high values between, ranking from 0.55 for T1 to 0.92 for T2. We remark that the model is well represented according to the Wald test; in fact, it shows significance at 1% level for all treatments. We also observe that the difference among subjects do not contribute to explain the unexplained variance for decisions in all treatments ($\rho = \sigma_u^2/(\sigma_u^2 + \sigma_\varepsilon^2) = 0$.

Given the estimated decision rules used by our subjects we can simulate it and compare it with the actual behavior. In the simulated behavior, we insert the estimated decision rule into the same model of the experiment and observe the behavior over time. To showcase our estimations, we selected regressions with the highest r^2

and where all the coefficients were significant in the OLS estimation. **Error! Reference source not found.** presents these simulations. We observe that the proposed heuristic replicates, to some extent, the pattern of behavior in all treatments. The simulations are also consistent with the underperformance previously described, given the over capacity with respect to the optimal for all cases. Such consistency is also observed for the average values of the estimated parameters compared with the average capacity across treatments (see Appendix 3). In similar fashion, we present the behavior of the overall estimated decision rule using our panel data GLS (?) estimation.

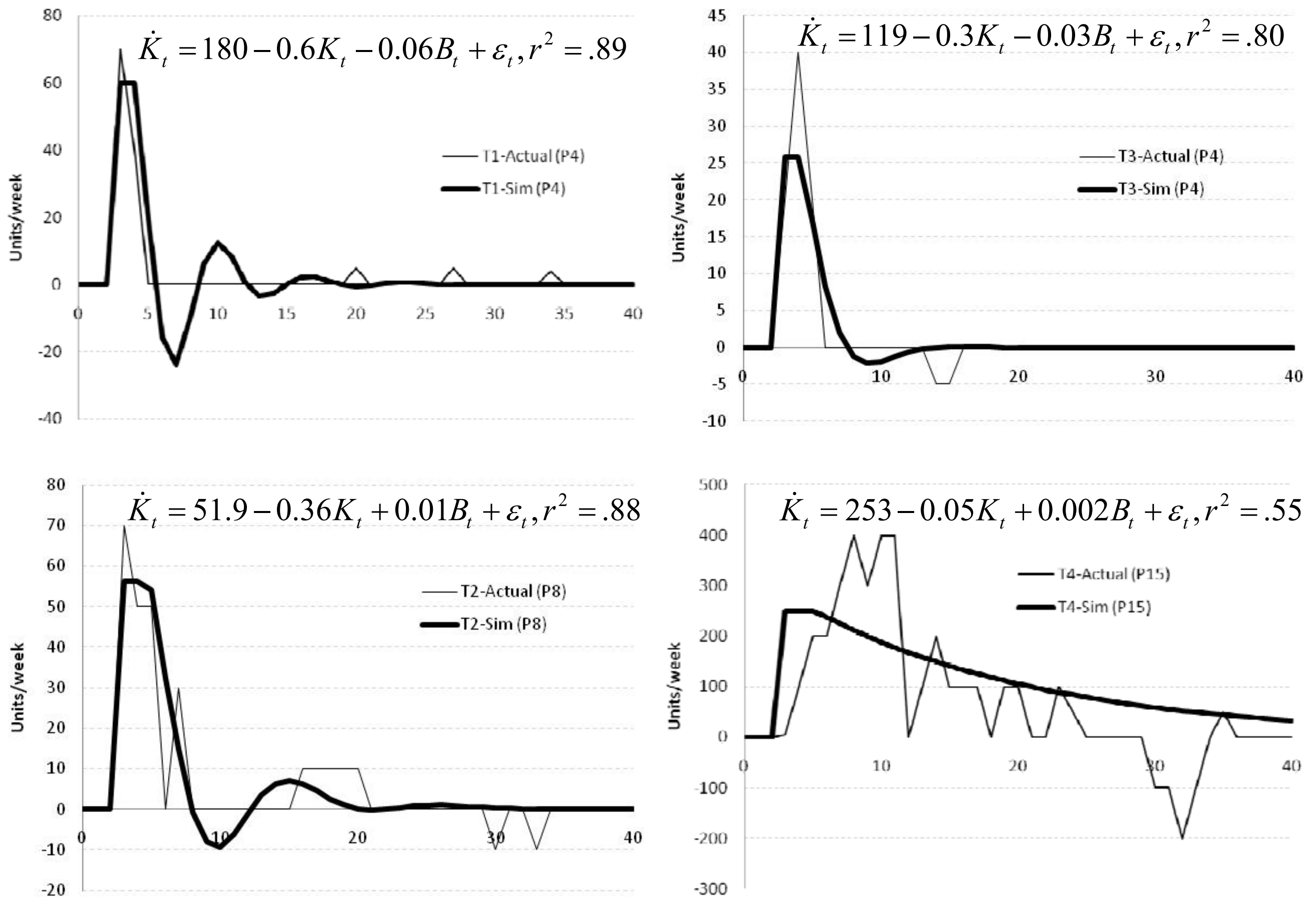


Figure 7. Simulation of the proposed heuristic and actual decisions for selected subjects in each treatment (subject ID in parenthesis).

DISCUSSION AND FURTHER RESEARCH

In this paper we characterized the optimal supplier capacity investment decisions in response to inflated demand, when the supplier cost function includes own capacity, change in capacity and order backlog. The optimal capacity investment function follows an exponential decay. The initial investment in capacity should be maximum at the beginning, exponentially decreasing to zero as times elapses. The optimal function is influenced by retailer order aggressiveness and capacity acquisition delays. The aggressiveness retailer order inflation affects the height of the optimal initial investment in capacity. Capacity acquisition delays increase the duration of the optimal capacity investment function.

In a laboratory experiment where participants make capacity investment decisions for a supplier faced with inflated retailer orders, we test how their decisions compare to the optimal result. We find that participants capacity investment decisions deviate widely from the normative result and that overall costs are far from optimal. Comparison between the optimal capacity investment decisions and the actual participants' decisions obtained through the experiment contributes to our understanding of supplier behavior during inflated retailer demand triggered by supply shortages.

Our experimental results show that participants overinvest in capacity, investing too much for too long, and subsequently they divest perceived capacity excesses. While this cycle of capacity overinvestment and divestment is attenuated over time, participants in general fail to sufficiently divest capacity, terminating the experiment with excess capacity. In addition, the peak in participants' capacity investment decision tends to occur earlier in treatments with shorter capacity acquisition delays. Also, capacity investment decisions are more variable and take longer to settle in treatments with higher retailer order aggressiveness. In general, participants' decisions are more stable and final costs are closer to optimal in simpler treatments (short capacity acquisition delays and low retailer order aggressiveness) and more unstable in more complicated ones.

The experimental results on participants' costs provide clues about the sources of underperformance. For instance, the results highlight that costs in low order aggressiveness treatments (T1 and T2) incur the largest fraction of costs through changes in capacity (*KC*) and that costs in high order aggressiveness treatments (T3 and T4) incur the majority of costs by maintaining a high backlog of orders (*B*). Costs in treatments (T1 and T2) capture the inherent complexity of the task, causing subjects to implement too many costly changes in capacity. In contrast, costs in treatments (T3 and T4) capture the inherent complexity of managing backlog, when subjects fail to properly invest in capacity to control backlog early letting the positive feedback loop of retailer order inflation drive the system dynamics.

By econometrically testing two decision heuristics, we find that subjects use a simple anchoring and adjustment heuristic to decide how to invest in capacity, with mixed quality of results. Individual regressions show negative relationships for orders with respect to backlog of orders (*B*)consistent with our expectations, but mixed results with respect to capacity (*K*) and more than 40% of r^2 values are larger than 0.40. We also structured the data as a panel (cross-sectional time-series) in order to increases the efficiency of the estimations and improve the representativeness of the decision rule. Estimations of panel data have shown that the coefficients of the backlog were not significant for all treatments except for T3, but coefficient of the capacity were both positive and significant as expected. Thus, the heuristic used bases the change in capacity (*KC*) more on a forecast of demand, rather than desired shipments. We tested this hypothesis and found it that it provides a better fit to the data that a heuristic that bases the investment in capacity on desired capacity. The model is well represented according to the Wald test and we observed that the difference among subjects do not contribute to explain the unexplained variance.

A number of researchers (e.g. Kaminsky and Simchi-Levi 1998, Gupta, Steckel and Banerji 1998) have analyzed policies (e.g., centralizing ordering decisions, reducing order lead-times, and sharing Point-of-Sales (POS) data) for reducing demand variability. Particularly important to demand bubbles is the availability of POS data. If suppliers had access to such data it is arguable that they would not be facing such harsh conditions since they could distinguish true demand from customer-inflated demand. Nevertheless, this situation has not been observed. The suppliers (in the case, experimental subjects) were informed about the real customers demand. Suppliers might have based capacity decisions on direct customer demand, but customers inflate orders more aggressively.

According to the precept of parallelism, the "propositions about the behavior of individuals and the performance of the institutions that have been tested in laboratory microeconomics apply also to nonlaboratory microeconomies where similar *cetiris paribus* conditions hold." (Smith, 1982 p. 936). In order to accomplish this precept the experiment requires an external validity. Our experiment is grounded into a model developed from the feedback structures of the real system, and has been formally tested in terms of both structure and behavior. Although the experiment is not a generalized problem for supply chain management, it indeed is representative of supply chains where speculative demand bubbles or phantom demand take place. Moreover, the typical behavior observed in the real industry such as microchips, is similar to the typical behavior presented in Figure . The general impression is pattern where a shock in demand, plus the over-ordering effect or phantom demand, leads to increase in capacity which at the end is overcapacity.

Experimentation science remarks that almost all experiment calls for a new experiment (Smith, 1982). In this sense, a number of new treatments and new experiments would help to improve the understanding of our particular case of supply chain. On the one hand, additional treatments could help to capture the truly rational decision from participants, the capacity acquisition delay should have been zero (i.e. a change of capacity in the current week would take place in the immediately following week). Analogously, perhaps a better normative benchmark would account for the actual reaction of suppliers when the retailers are not inflating their orders. Thus, new treatments could consider the simplest case with neutral retailer order capacity for different investment delays, as well as the effect of no investment delay for different retailer order aggressiveness.
On the other hand, new experiments can consider retailer's decision experiments and analysis, where change in capacity is simulated with the proposed heuristic presented here. A more complex experiment is a joint decisions supplier and retailer experiment and analysis, where new hypotheses should be formulated.

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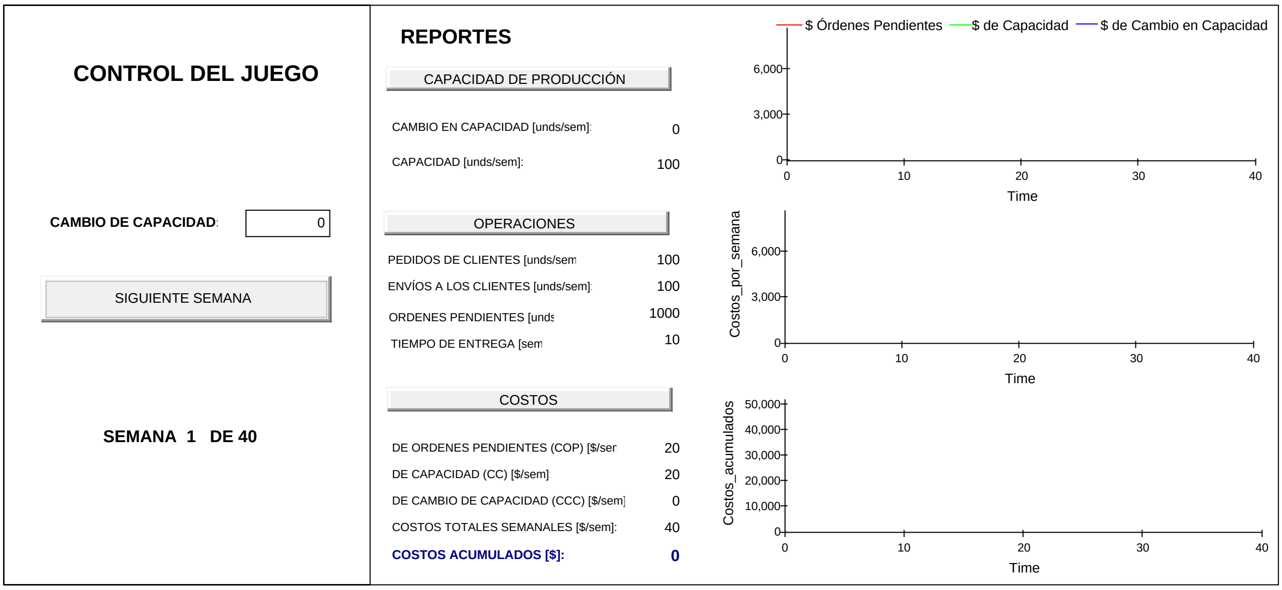
Appendix 1. Computer interface.



Appendix 2. Instructions for treatment T1 (In Spanish).

INSTRUCCIONES

POR FAVOR NO TOCAR EL COMPUTADOR HASTA QUE NO SE LE INDIQUE

Bienvenido, a partir de este momento usted hace parte de un experimento de toma de decisiones, en el cual asumirá el papel de gerente de una compañía. Su responsabilidad es **minimizar los costos acumulados** al final de la simulación del juego (40 semanas), y de acuerdo a su desempeño obtendrá un pago en dinero efectivo.

Su decisión semanal es definir cuántas unidades ***incrementar o disminuir*** la capacidad de producción, con el fin de cubrir toda la demanda de sus clientes (en el juego, esta decisión se toma en la casilla ubicada al frente de "*Cambio en Capacidad*"). La capacidad inicial de producción es de 100 unidades por semana; decidir 10 unidades en *"Cambio en Capacidad*" en la semana 5, significa una capacidad disponible en la semana 6 de 110 unidades. Decidir -5 unidades en "*Cambio en Capacidad*" en la semana 7, significa una capacidad disponible en la semana 8 de 95 unidades.

Se incurre en costos cada semana por tres componentes:

1. Costo por Órdenes Pendientes (COP): es el costo por no servir a sus clientes inmediatamente.
Se determina semanalmente así:

$$COP = 20 * \left(\frac{Órdenes\ \ Pendientes}{1000} \right)^2$$

Con una cantidad inicial de pedidos por realizar de 1000 unidades, este costo en la primera semana es de $20.

2. Costo de Capacidad (CC): es un costo fijo por el mantenimiento de la capacidad productiva existente. Se determina semanalmente así:

$$CC = 20 * \left(\frac{Capacidad}{100} \right)^2$$

Con una capacidad inicial de 100 unidades/semana, el costo en la primera semana es de $20.

3. Costo de Cambio en Capacidad (CCC): es el costo de aumentar o disminuir la capacidad disponible. Se determina semanalmente así:

$$CCC = 2 * (Cambio\ \ en\ \ Capacidad)^2$$

El costo unitario del cambio en capacidad es 2$/ (unidad/semana), pero las primeras 3 semanas no hay cambio en capacidad, por lo tanto el CCC es $0.

De esta manera, el costo total acumulado CTA es la suma de estos costos en toda la simulación, así:

$$CTA = \sum_{t=1}^{40} \left(COP_t + CC_t + CCC_t \right)$$

Inicialmente, los clientes ordenan 100 unidades por semana, lo cual le permite a usted conservar un tiempo de entrega objetivo de 10 semanas como condición inicial. Recientemente, aplicaciones novedosas de sus productos crearon un aumento en su demanda. Usted estima que el incremento en la demanda será permanente y del orden de 20 unidades por semana. Dado que usted no estaba atento a estas nuevas aplicaciones, el aumento en la demanda lo tomó por sorpresa y se da cuenta de que su tiempo de entrega también está empezando a incrementarse. De su conocimiento de la industria usted sabe que sus clientes podrían reaccionar a estos crecientes retardos en las entregas, haciendo pedidos que están inflados.
Usted iniciara por 3 semanas decidiendo 0 unidades como periodo de aprendizaje. Después su tarea es manejar la compañía durante la simulación, decidiendo en cuánto aumentar o disminuir la capacidad mientras que minimiza el costo total acumulado CTA.

PAGO: El pago será en efectivo al final del experimento. Corresponde a una suma por participación de \$10000 mas una suma variable entre \$0 y \$30000 en función del CTA, a menor costo mayor pago.

NOTA: Por favor no divulgar información del experimento con sus compañeros para no perder la validez científica del experimento.

GLOSARIO
(ACERCA DE LOS RESULTADOS QUE SE OBSERVAN EN "REPORTES")

Sección de Capacidad de Producción: Da información de la capacidad de producción del proveedor (usted).

- Cambio en capacidad (unidades/semana): Esta es la decisión semanal que usted (proveedor) debe tomar para incrementar o disminuir su capacidad. Seleccionando un valor de, por ejemplo, x unidades, usted incrementa x unidades al nivel actual de capacidad, el cual se hará efectivo en 1 semana. Así, si su capacidad era de y unidades antes de su decisión, después de ésta su nueva capacidad será de $x + y$.
- Capacidad (unidades/semana): Es su capacidad de producción disponible, la cual le permite enviar los pedidos a los clientes. El valor inicial de la capacidad para su planta es de 100 unidades/semana.

Sección de Operaciones: Da información de sus operaciones.

- Pedidos de clientes (unidades/semana): Son las órdenes que usted recibe de sus clientes. Esta es la demanda que se debe cubrir. El nivel normal de pedidos es de 100 unidades/semana.
- Envíos a los clientes (unidades/semana): Son los envíos a sus clientes. Los envíos están limitados por su capacidad de producción. Inicialmente usted puede enviar 100 unidades/semana a sus clientes.
- Órdenes pendientes (unidades): acumulan la diferencia entre las órdenes y los envíos hechos a los clientes en el tiempo. Inicialmente usted tiene una cantidad acumulada de pedidos por realizar de 1000 unidades.
- Tiempo de entrega (semanas): Es el tiempo de entrega promedio en que las órdenes se quedan sin realizar, desde el momento en que son hechas por los clientes hasta el momento en que usted puede enviárselas. El tiempo de entrega inicial es de 10 semanas.
- Tiempo de entrega deseado (semanas): El tiempo de entrega objetivo que usted desearía mantener es de 10 semanas.

Sección de Costos: Da información acerca de cada componente de sus costos:

- Costo de órdenes pendientes (\$/semana)
- Costo de capacidad (\$/semana)
- Costo de cambio en la capacidad (\$/semana)
- Costos totales (\$/semana): Es la suma de los tres componentes de los costos cada semana.
- Costos acumulados (\$): Es el costo total acumulado en el tiempo.

Appendix 3. Simulation of the proposed heuristic for average values of the estimated parameters compared with the average capacity in each treatment.