"I'm not hoarding, I'm just stocking up before the hoarders get here"

Behavioral operations management requires integration of multiple disciplinary perspectives and methods, including formal modeling, laboratory experiments, fieldwork, and large-sample empirical studies. Here we report an experimental study with the Beer Distribution Game to explore the phenomenon of phantom orders. Phantom orders arise in real supply chains when suppliers are unable to fill orders on time. Customers respond to product shortages by increasing orders and ordering through different channels in an attempt to gain a larger share of the shrinking production pie. These phantom orders cause still longer delivery times and smaller allocations: a positive feedback through which scarcity becomes self-reinforcing. Suppliers, often unaware of the underlying demand, respond by increasing output. As allocations increase customers cancel their phantom orders, leaving suppliers and distributors with large surplus stocks. Phantom ordering is common in supply chains including semiconductors, computers, pulp and paper, chemicals, and others, and played a major role in the collapse of the technology bubble in 2001. As the title indicates, such behavior can be rational, as multiple customers compete for limited supply. Here we examine the behavior of participants in the beer distribution game for evidence of phantom ordering. Phantom ordering is never a rational response to shortage in the experiment because there is only one customer for each supplier, no randomness, no production capacity limit, and, in this implementation, customer demand is constant and publicly announced to all participants. Yet we find that a significant minority exhibits phantom ordering. Estimated decision rules show that these participants increase their orders when delivery times increase, though such orders

raise costs and reduce the reward earned by each participant. We speculate that the urge to hoard evolved early in human history as a locally rational response to scarce resources, and that the brain center responsible for the hoarding response is likely to be distinct from the loci of economic decision making.

1. Introduction

Supply chain managers often face shortages and put their customers on allocation. Customers react to these shortages by ordering more than they need. Misled by this steep increase in orders, suppliers ramp up production. However, as customers begin to receive the orders they need, they cancel their speculative orders and leave the supplier with excess inventory and low prices. This is a widely known phenomenon in supply chains and has been given different names in the literature such as phantom ordering (Sterman 2000), rationing and shortage gaming (Lee et. al. 1997a), double ordering (Armony and Plambeck 2005) and hoarding.

Phantom ordering is prevalent across many industries. Industries with long lead times (chemicals, pulp and paper, semiconductor, high-tech), hot consumer products (toys, games, consumer electronics) and vital products subject to supply shocks (gasoline, drugs, food/household supplies) provide several examples of phantom ordering. Consequences of phantom ordering might be severe. In 2001, Cisco wrote off \$2.2 billion worth of inventory due to cancelled orders (Armony and Plambeck 2005). Phantom ordering for Hewlett-Packard's LaserJet III printers cost the company millions of dollars in the 90's (Lee et. al. 1997a).

Phantom ordering has been known for a long time by both practitioners and academics (Mitchell 1924, Forrester 1961) and attracted considerable interest more recently. Mitchell described the phenomenon in 1924 as follows:

"Retailers find that there is a shortage of merchandise at their sources of supply. Manufacturers inform them that it is with great regret that they are able to fill their orders only to the extent of 80 per cent… However, retailers, having been disappointed in deliveries … are not going to be caught that way again… Next season, if they want 90 units of an article, they order 100, so as to be sure, each, of getting the 90… Furthermore, to make doubly sure, each merchant spreads his orders over more sources of supply." (Mitchell, 1924).

More recently, Cachon and Lariviere (1999) and Lee et. al. (1997b) showed that phantom ordering or shortage gaming is in fact the rational thing to do for customers in some settings when there is horizontal competition between customers. Sterman (2000) presented a simulation model that was used to deal with phantom ordering by an electronics company that faced phantom ordering very frequently. Armony and Plambeck (2005) investigated the consequences of not accounting for double orders.

Rational factors play an important role in phantom ordering in many cases. This is especially true if multiple customers compete for same product, orders can be cancelled at low cost, there is uncertainty about final demand or final demand is unknown, system is subject to stochastic shocks and capacity constraints may limit production. In this paper, we remove all these operational reasons and test the existence of complementary behavioral causes of phantom ordering stemming from the use of heuristics or from bounded rationality. We use a tightly controlled experimental setting (the Beer Game) that eliminates all the above mentioned rational causes for phantom ordering.

Beer Game has been used by several operations management researchers since it provides a controlled environment to test behavior. It has been used to understand the behavioral reasons of bullwhip effect, the impact of POS data sharing, inventory level data sharing and learning and communication on bullwhip effect (Sterman 1989, Croson et. al. 2006, Croson and Donohue 2003, Steckel et. al. 2004, Croson and Donohue 2006, Wu and Katok 2006). Croson et. al. (2006) eliminate all four operational causes of bullwhip effect identified by Lee et. al. (1997a) and show that bullwhip effect still exists due to perceived coordination risk and the role of coordination stock. This is a striking finding because in their setting, end-customer demand is 4 all through the game and the participants are informed about this before the game starts. In this paper, we use the same data set to test the hypothesis that phantom ordering exists in the Beer Game.

In the game, participants receive their orders 4 weeks after they place them if their supplier is in stock[1]. If the supplier of a participant stocks out, delivery delay goes up just like in real supply chains. In real supply chains, this increase in shipment lead time of supplier is the trigger for phantom ordering. As mentioned before, this reaction might be the rational response, especially if there is horizontal competition and it is possible to

[1] Note that delivery delay is always 3 weeks for factories because there's no constraint on their resources for brewing the beer.

cancel orders with low cost. However, in this version of the Beer Game, orders cannot be cancelled and there is no horizontal competition for the participants' immediate supplier. Furthermore, there is no capacity constraint for production and all participants know that the end customer demand is fixed. Hence, phantom ordering is not a rational response to shortages in the game. Phantom orders will either be delivered by the upstream participants and incur inventory holding cost to the participant that ordered them, or will not be delivered and incur backlog cost to the upstream participants. Total team cost increases in both cases. Since participants are rewarded according to their total team cost, phantom orders decrease the reward of the participant that placed them along with the other team members.

This paper contributes to the literature in several ways. We present decision rules that reflect bounded rationality and depend only on information cues available to the participants and use these heuristics to test the existence of phantom ordering empirically. Econometric estimation results show that these heuristics explain the behavior of some participants much better than other heuristics used in the literature. Traditional heuristics are not able to explain the behavior of these participants and conclude that they are outliers that place orders randomly without a consistent pattern. Moreover, we find that a significant minority react to scarcity by placing phantom orders even if it is not rational to do so. We identify the reinforcing loops that generate this behavior. These loops have the potential to destabilize the system very rapidly. This is an important finding that shows the need for further research on the behavioral reasons of this important real life phenomenon and ways to mitigate it. Finally, we suggest new avenues of research for understanding the behavioral reasons of phantom ordering in light of our empirical results, participant responses to post-game questionnaire and recent findings of neuroeconomics and psychiatry literatures.

In the following sections, we describe the experimental setting, decision rules used to test the existence of phantom ordering and empirical results.

2. Experiment

The experiment was run for 48 weeks using a web based simulator. The web-based simulator was used to ensure that the results do not contain any accounting or measurement errors. As in the classical version of the beer game (Sterman 1989), inventory holding costs were $0.5/week and backlog costs were $1/week. However, unlike the classical game, customer demand was constant: equal to 4 cases per week and this information was announced to all participants. Before the start of the game, it was confirmed with a quiz that the participants understood this fact. Furthermore, realization of the end customer demand (4 cases) was displayed on each participant's screen at all rounds. After the game, but before receiving payment, participants were asked to complete a questionnaire to reflect their opinion on their strategy, their teammates' strategy and additional information that they think would improve their performance. For a detailed description of the experimental setting, payment scheme and questionnaire, see Croson et. al. (2006).

The supply chain was initialized in equilibrium and in some treatment groups initial inventory was equal to the optimal level of 0. Under these circumstances, the optimal strategy is clearly to order 4 cases per week throughout the game. However, we still observe oscillation and amplification for most participants (See Figure 1 for a typical team).

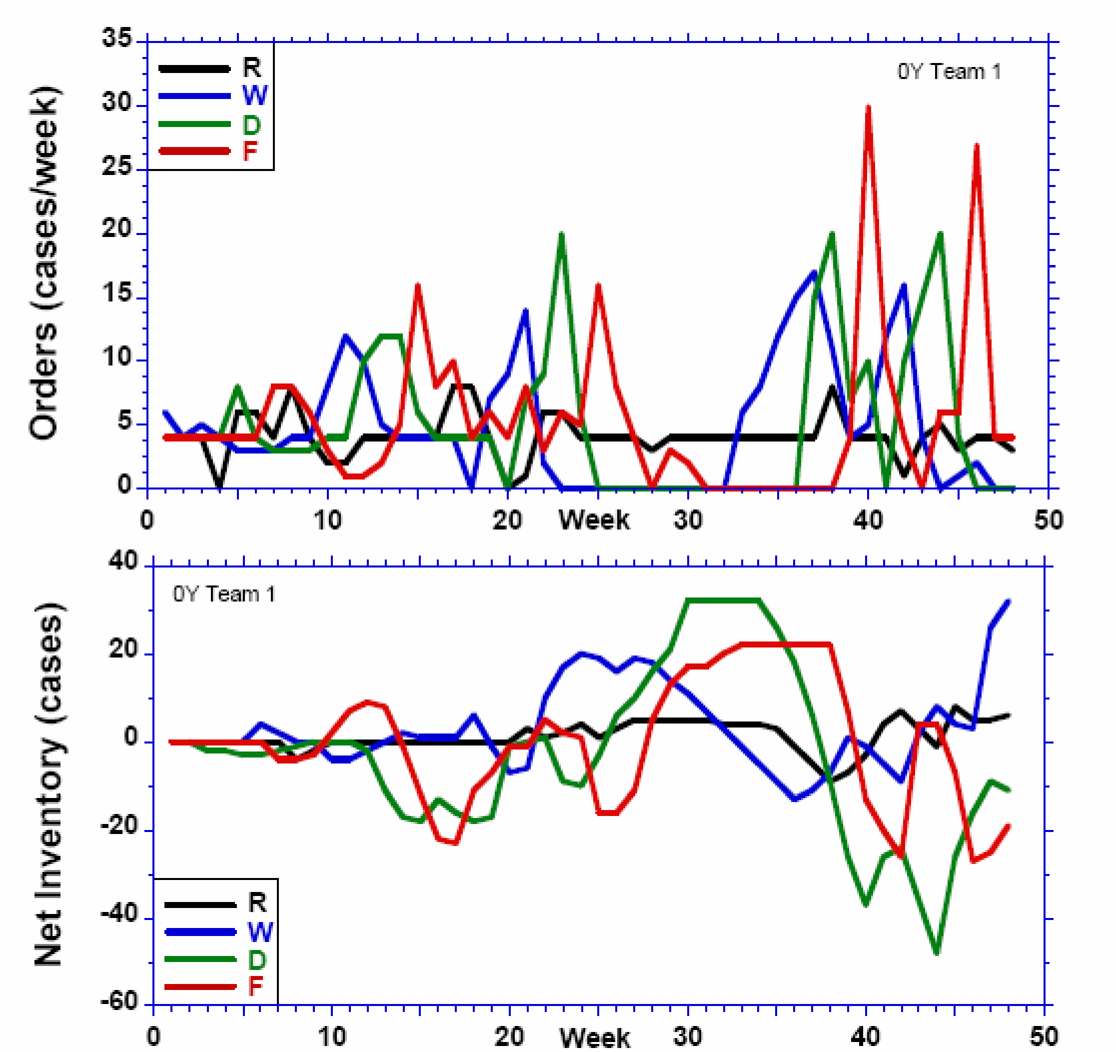


Figure 1: Orders placed and net inventory of a typical team

Only 9 participants out of the 240 participants participated in the experiment ordered exactly 4 cases per week throughout the game. Maximum orders placed by a participant in one week were 40000 cases per week (See Figure 2). Standard deviation of all orders placed by all participants was 761.86 cases per week. Croson et. al. (2006) find that participants deviate from the optimum order level of 4 cases/week and perturb the system from equilibrium because they want to hold coordination stock against the risk that other participants will deviate from optimal behavior.

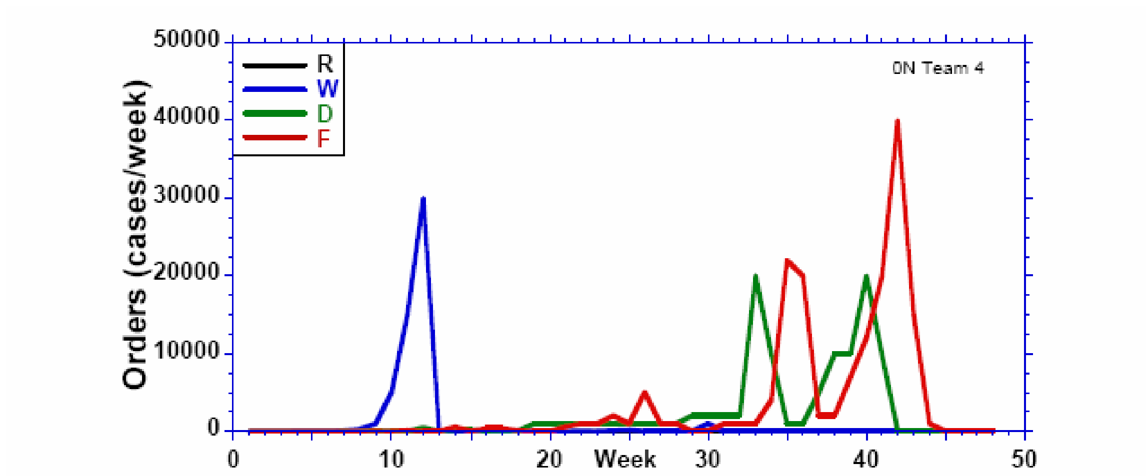


Figure 2: Orders placed by the team that had the highest order in a given week

3. Experimental Results

Following Sterman (1989), we test our hypotheses by estimating dynamic decision rules that rely only on information cues available to the participants. We start with estimating the decision rule used by Sterman (1989). The decision rule is based on the anchoring and adjustment heuristic (Tversky and Kahneman 1974). This rule uses expected customer orders as the anchor and adjusts for the discrepancy between desired inventory and net inventory and the discrepancy between the desired supply line of beer on order and actual supply line. Supply line means orders placed but not yet received by the participant. In the formulation, we use a non-negativity constraint since the orders cannot be negative:

$$O_t = MAX\,(0, CO_t^e + AS_t + ASL_t) + \varepsilon_t$$

CO^e represents orders expected from the participant's customer next period. AS is the adjustment made to reduce the discrepancy between desired inventory and inventory and ASL is the adjustment made to reduce the discrepancy between desired supply line and actual supply line. ε is the additive disturbance term. We formulated the expected customer orders using exponential smoothing:

$$CO_t^e = \theta * IO_{t-1} + (1-\theta) * CO_{t-1}^e$$

where IO is actual incoming orders. This equation represents the possibility that participants' forecast on incoming orders respond to the actual orders they receive from their customers.

Inventory adjustment is linear in the discrepancy between desired inventory (S*) and net inventory (S):

$$AS_t = \alpha_S (S_t^* - S_t)$$

where α_S is the fraction of inventory discrepancy ordered each period. Similarly, the supply line adjustment formulation is also linear in the discrepancy between the desired supply line (SL*) and the actual supply line (SL):

$$ASL_t = \alpha_{SL} (SL_t^* - SL_t)$$

where α_{SL} is the fraction of supply line discrepancy ordered each period.

So, orders placed equals:

$$O_t = MAX\,(0, CO_t^e + \alpha_s (S_t^* - S_t) + \alpha_{SL}(SL_t^* - SL_t) + \varepsilon_t)$$

This decision rule assumes that the desired inventory (S*) and desired supply line (SL*) are constant. Since customer demand is constant, participants are informed about this fact and the chain is initialized at equilibrium, it seems reasonable to assume that desired inventory and desired supply line are fixed. Obviously, the optimum desired inventory is 0 cases since the customer demand is constant and known. Optimum level of desired supply line is customer demand (4 cases/week) times normal delivery delay. Note that this heuristic does not react to supplier shortages by increasing desired inventory or desired supply line, so it does not represent phantom ordering.

Assuming S* and SL* are constant and defining $\beta = \alpha_{SL}/\alpha_S$ and S' = S* + βSL*, the equations to be estimated become:

$$O_t = MAX\,(0, CO_t^e + \alpha_s (S' - S_t - \beta * SL_t) + \varepsilon_t)$$

$$CO_t^e = \theta * IO_{t-1} + (1-\theta) * CO_{t-1}^e$$

So, the parameters we need to estimate are: θ (for CO_t^e), α_s, β and S'. β is the fraction of supply line participants take into account while placing orders. Since the participants should take into account the supply line as much as their on-hand inventory, the optimum value of β is 1. The optimum value of α_S is also 1 because they should try to reduce the entire inventory discrepancy each period.

We minimize the sum of squared errors between actual orders, AO_t, and model orders, O_t, to estimate the parameters.

$$\underset{\alpha_s,\beta,\theta,S'}{Min} \sum_{t=1}^{48} (AO_t - O_t)^2$$

subject to

$$0 \le \theta \le 1$$

$$0 \le \alpha_s \le 1$$

$$0 \le \beta \le 1$$

$$0 \le S'$$

Estimation results for retailers, wholesalers and distributors are presented in Table 1. Median fraction of inventory discrepancy corrected at each time period (α_s) is 0.28 and median fraction of supply line participants take into account (β) is 0.16. Both values are far below the optimal value of 1. So, even if the customer demand is constant and this is known by the participants, most of them ignore the supply line of goods on-order. β is significantly smaller than 1 for 72% of the participants and α_s is significantly smaller than 1 for 81% of the participants. β is not significantly bigger than 0 for 70% of the participants.

Overall, the decision rule captures the orders placed by participants successfully. Median R^2 is 0.43 and median Root Mean Square Error (RMSE) is 2.72 cases per week. Since standard deviation of orders placed is 761.86 cases per week, median RMSE value indicates a good fit.

Table 1: Estimation results for the decision rule with fixed desired inventory and desired supply line[2]

	θ	α_s	β	S'	R^2	RMSE
Mean	0.32	0.41	0.30	23.25	0.43	92.36
Median	0.13	0.28	0.16	4.58	0.43	2.72
N	109	171	163	163	171	171

As expressed above, the decision rule fits the data well. However, for some participants the fit is very poor. See Appendix 1 for the plots of these participants' actual orders and model output. One explanation might be that these participants did not understand the game or they were not motivated and they placed their orders randomly without following any pattern or heuristic. However, another explanation might be that their orders were not completely random, instead they used some heuristics that deviate from rationality under the pressure of shortages. Hence, we relaxed the assumptions that desired inventory and desired supply line are fixed by using alternative decision rules with endogenous desired supply line (SL*) and desired inventory (S*) formulations. A participant might want to have enough beer in the supply line that will serve the customer for a time period that equals the expected time it takes the supplier to deliver the beer.

[2] Note that the number of θ, β and S' estimates are less than the number of participants. This is because it is not possible to estimate θ if incoming orders are constant and it is not possible to estimate β and S' if α_s is equal to 0.

This implies that if the orders they receive from their customer increase or they think that their supplier is not always able to ship their orders on time, they might increase the amount of beer they would like to have in pipeline. By the same token, participants might adjust their safety stock or coordination stock dynamically according to the orders they receive and the perceived reliability of their supplier.

Post-play questionnaire shows that participants do pay attention to the reliability of shipments they receive from their immediate supplier and adjust their ordering policies accordingly. Incoming orders also have an influence on their desired inventory and desired supply line. When they were asked to explain how they decided how much to order each week, some participants said:

> *"I decided to order based on my inventory. I tried to keep my inventory close to zero, but then I began to find out that I didn't always receive what I ordered, so then I tried to have a little more than 0 in my inventory." [Retailer]*

> *"Try to use the base-stock policy. Base-stock level equal to the lead time demand=12, since I am in the manufacturer with 3 weeks delay. The incoming orders may force me to raise the inventory." [Manufacturer]*

> *"I couldn't get the hang of having orders I placed fours weeks ago come in four weeks later. It was hard to look ahead and figure out how much I would need." [Distributor]*

“I tried to keep it so I had a 2 week inventory available to me at all times.” [Retailer]

When they were asked what caused their inventory or backlog to behave as it did, some participants said:

“The supplier not fulfilling the order in the time you wanted it to” [Retailer]

“I did not recieve the amount of beer as quickly as I thought I would have.” [Retailer]

“I couldn't predict when I would recieve the orders” [Retailer]

“The unpredictableness of the shipment I would receive was the cause of my backlog or inventory. “ [Retailer]

“They shipped as less as they could.” [Retailer]

“The distributor was not capable to deliver what I ordered.“ [Wholesaler]

“My wholesaler couldn't cover my inventory when i had a low inventory. i'm not sure why they didn't plan to have enough on hand even thought hey knew that i would need 4 per week after a few weeks.“ [Retailer]

“The lack of steady shippments.” [Retailer]

“Uncertainty of what distributor sending, uneven amounts.” [Wholesaler]

“Insufficient orders being filled at times.” [Retailer]

“My provider sent me some bad shipments some weeks.” [Wholesaler]

“The inventory of my supplier affected my inventory/backlog.” [Retailer]

Some participants responded to the question “What information would have helped you do better?” as:

“knowing how many kegs would be shipped, you knew how many you ordered and how many weeks but you didn't know how many they would ship at a time.” [Retailer]

“i was very confused about how logn it woudl take for my shipments to arrive. it was difficult to keep track.” [Retailer]

“To know how long each order would take to be shipped back to me.” [Retailer]

A retailer said:

"I started out with a strategy but, the line of supply was slower than i expect so i got in a hole, and it was tought to get out of"

A manufacturer, whose delivery delay is fixed, explained his/her teammates' behavior as:

"He or she is a nut. Had no sense about inventory. Once in backlog, no patience to wait for a little while… Panic. Non-sense."

"The wholesaler panic first raised two orders of 20 units in a row. This is unnecessary. When the shippment is not enough, place another big one is extremely stupid. End up with huge inventory. Then the distributor also panic too. No sense about the orders"

He or she responded to the question: "What information would have helped you do better?" as:

"I guess a reminder for some players that, "they will have a big order arrive do need to panic" will be very helpful."

These responses show that participants' desired inventory and desired supply line changes according to the expected delivery delay from the supplier and expected incoming orders from the immediate customer. However, both questionnaire responses and orders placed by different participants show that the magnitude and nature of the reaction is not identical and changes drastically from participant to participant since some participants are more prone to panicking than other ones. Hence, we estimated a set of alternative decision rules for each participant to find out which one explains the variation for that participant the best. Forrester (1961) and Sterman (2000) provide heuristics that accommodates the idea that desired supply line and desired inventory is dynamic and updated with respect to changes in delivery delay or incoming orders. These heuristics depend only on information cues available to the decision makers and are boundedly rational.

In the alternative decision rules, desired supply line is formulated according to the following equation:

$$SL_t^* = MAX(0, EDD_t * DesiredAcquisitionRate_t) \quad (1)$$

where EDD is the expected delivery delay. It equals the expected delay between the time participant places the order and receives the goods. If the supplier stocks out, the delivery delay would exceed the normal delivery delay. In that case, the expected delivery delay would also increase. This formulation is in line with the ones used by Forrester (1961, Chapter 15) and Sterman (2000, Chapter 17).

In equation (1), desired supply line is formulated as the amount of goods that will cover the desired acquisition rate for a time period equal to the expected delivery delay. We used one formulation for expected delivery delay (EDD_t) and two formulations for desired acquisition rate (DAR_t). As mentioned above, expected delivery delay might change over time because if the participants receive fewer shipments than what they expect, they would figure out that the supplier has stocked out and it will take longer to receive the orders than the normal delivery delay. This concept is also known in the literature as rationing and shortage gaming (Lee et. al. 1997a).

Our formulation is flexible in the sense that the expected delivery delay might be completely dynamic without any anchoring to the normal delivery delay, it might be always equal to normal delivery delay in which case the participant is not phantom ordering at all or it might be a mixture of the two. This is formulated by making the expected delivery delay a weighted average of perceived delivery delay (PDD) and normal delivery delay (NDD). Perceived delivery delay is based on Little's law. According to Little's law, in steady state average time it takes to receive shipments is equal to the amount of beer in supply line divided by shipments received. So, expected delivery delay is formulated as:

$$EDD = w*NDD + (1-w)*PDD$$

where w is the weight on normal delivery delay and it is a parameter to be estimated.

If w is 1, expected delivery delay is always equal to normal delivery delay, so the participant does not place phantom orders. If w is less than 1, participant is paying some attention to the actual delivery delay and updates his or her expectations about the delivery delay. To test the hypothesis that the participant places phantom orders or not, we test the hypothesis that w is equal to 1. If w is significantly smaller than 1, we conclude that the participant places phantom orders. Note that there are cases in which the estimated value of w is smaller than 1 but the difference is not statistically significant. In those cases, we do not classify that participant as a phantom orderer.

Delivery delay cannot be smaller than the normal delivery delay due to the physics of the system, so perceived delivery delay is:

$$PDD = MAX(NDD, SL/Shipments\ Received)$$

Factories do not have suppliers and delivery delay is always three weeks for them. So, EDD is fixed for the factories all the time. Thus, we do not include factories in any of the analysis results presented in this paper.

We used two alternatives for Desired Acquisition Rate (DAR). First one assumes that participants adjust supply line according to expected loss rate. In this case, desired acquisition rate is equal to expected customer orders (CO^e).

$$DAR = CO^e$$

Second alternative assumes that in addition to the expected loss rate, participants also account for the temporary gaps between desired inventory and actual inventory while adjusting the supply line. This formulation is in line with the one proposed by Sterman (2000, Chapter 17). In the second case, the desired acquisition rate is:

$$DAR = CO^e + \alpha_s(S^*-S)$$

Some participants' questionnaire responses clearly indicate their tendency to keep a safety stock that is sufficient to cover demand for a fixed number or weeks. However, there are some other participants that imply that they updated their desired inventory level but they do not specify how. Some of the responses even imply panic. So, we used two alternative formulations for Desired Inventory (S*) to allow flexibility for both possibilities for each participant, namely panic and fixed inventory coverage:

$$S_t^* = EDD_t * CO_t^e$$

and

$$S_t^* = DesiredInventoryCoverage * CO_t^e$$

where Desired Inventory Coverage is a parameter to be estimated.

The first alternative suggests that besides the changes in incoming customer orders, changes in expected delivery delay also influence desired inventory. Second alternative suggests that there is a fixed desired inventory coverage that needs to be estimated econometrically and the participants update desired inventory only by considering the changes in incoming customer orders.

Updating the order decisions according to changing order levels from the customer is also given the name demand forecast updating in the literature (Lee et. al. 1997a). Unlike rationing and shortage gaming, in our experimental setting demand forecast updating might be the right thing to do in some cases since backlog costs more than holding inventory.

In brief, we estimate four decision rules for each participant: two alternatives for desired acquisition rate and two alternatives for desired inventory. We pick the alternative rule with the smallest RMSE and call it the best alternative decision rule for each participant. If RMSE of the best alternative decision rule is smaller than the RMSE of the original decision rule, we test the hypothesis that w is equal to 1 for that participant. If w is significantly smaller than 1, we classify the participant as a phantom orderer.

It's important to note that the variable expected delivery delay formulation implies the existence of a reinforcing loop: as orders placed goes up, supply line goes up. This increases the chance that supplier will stock out and expected delivery delay will go up. Hence, desired inventory and desired supply line go up increasing orders even further (See Figure 3). This reinforcing loop has the potential to destabilize the system very rapidly by increasing orders to very high amounts (Goncalves 2003) and might account for the progressive escalation of orders to very high levels for some participants shown in Appendix 1. Note that the original model with fixed desired inventory and supply line was not able to explain the rapid escalation of orders for those participants.

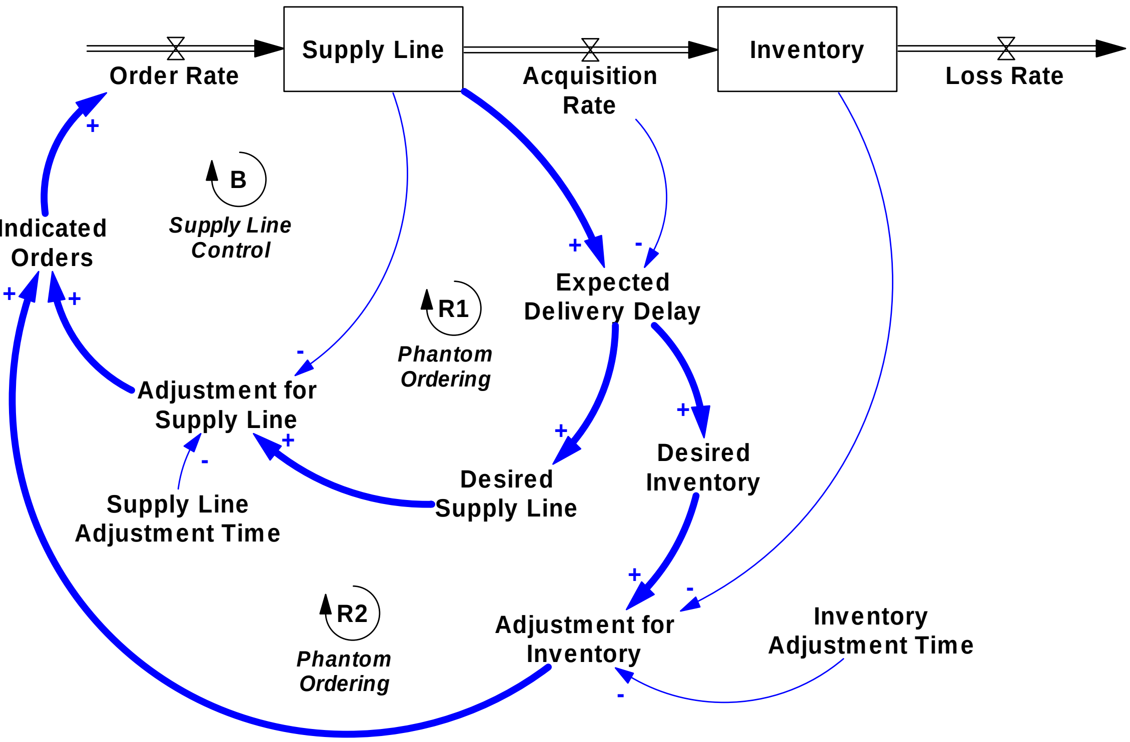


Figure 3: Phantom Ordering Loops

Conditions of the experiment strongly disfavor this reinforcing loop: Demand is constant, all participants are informed about this fact before the game started and game is initialized at equilibrium. Furthermore, participants know that they will receive their orders eventually since they do not compete against other parties as in real life. In real life, typically a supplier serves more than one customer and if the supplier can only ship less than the total of customer orders, customers cannot get all the orders they place. So, they might order more than what they need because they know that they will receive less than what they order. This is a rational behavior especially if orders can be cancelled at no cost. However, the fact that each supplier serves only one customer in our experimental setting disfavors phantom orders even further. Moreover, the rules of the game punish this type of behavior since it is not allowed to cancel orders. Phantom orders will either be delivered by the upstream participants and incur inventory holding cost to the participant that ordered them, or will not be delivered and incur backlog cost to the upstream participants. Total team cost increases in both cases. Since participants are rewarded according to their total team cost, phantom ordering is not the rational behavior in this context.

As mentioned above, we estimated four decision rules for each participant and picked the one with lowest RMSE as the best one. Composition of the best alternative formulations with respect to DAR and Desired Inventory are in Table 2. More than 70% of these participants try to maintain fixed inventory coverage rather than a floating one with respect to changing delivery delay. Desired acquisition rate alternatives are almost evenly split between the two formulations. Overall estimation results of best alternative formulation for each participant are presented in Table 3 along with the results of original model estimation. Results show that the overall fit statistics are virtually equivalent for the best alternative formulations and the original model, so alternative formulations do not lead to overall improvement. This is an expected result since the experimental conditions favor the original formulation. In fact, for half of the participants, even the best alternative formulation performs worse than the original model. This finding is illustrated in

Figure 4 which displays the ratio of original model RMSE to best alternative formulation's RMSE.

Table 2: Percentage of best alternative formulations

		Desired Acquisition Rate	
	Percent of Participants	CO^e	$CO^e + \alpha_s(S^*-S)$
Desired Inventory	EAL * DAR	12%	14%
	Desired Inv. Cov. * DAR	41%	32%

Table 3: Comparison of fit for the best alternative formulations and original model.

Results for original formulation	R^2	RMSE
Mean	0.43	92.36
Median	0.43	2.72
N	171	171

Results for best alternatives	R^2	RMSE
Mean	0.45	59.70
Median	0.44	2.69
N	171	171

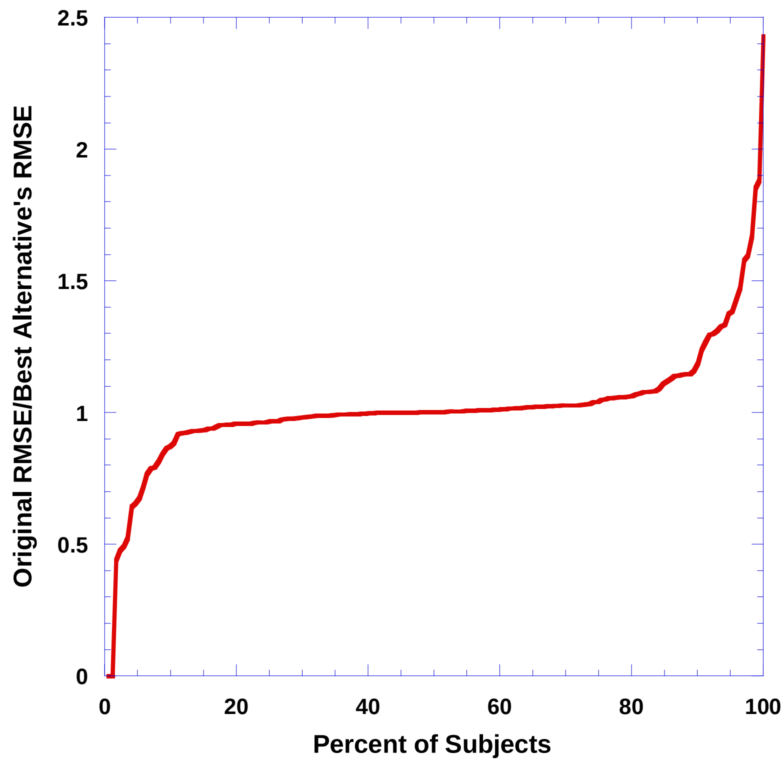


Figure 4: Ratio of Original RMSE to Best Alternative's RMSE

We see improvement of fit in terms of RMSE for 85 participants out of 171. Estimation results for the improved participants are presented in Table 4. Results show moderate improvement for these participants. Mean and median α_s values are higher for the original model whereas mean and median beta values are lower. This is an expected result because the original decision rule assumes that desired inventory and supply line does not react to increasing incoming orders or delivery delay. However, post-play questionnaire responses quoted above shows that this is a restrictive assumption for some participants. Original model is misspecified for these participants. To explain the exaggerated reaction of these participants to increasing incoming orders and expected delivery delay, original model yields upward biased alpha estimates that place orders more aggressively and downward biased beta estimates that imply more dramatic supply line ignoring.

Even though the alternative heuristics do not improve overall results, Figure 4 shows that for some participants these formulations lead to substantial improvement. Appendix 2 presents actual orders and simulated orders for some of these participants for both original formulation and best alternative formulation.

Table 4: Comparison of original model results vs. best alternative formulations results of participants for which alternative formulations lead to improvement.

a) Result for original estimates of improved participants

	θ	α_s	β	w	S'	Des. Inv. Cov.	R^2	RMSE
Mean	0.36	0.45	0.14	-	39.33	-	0.39	181.39
Median	0.19	0.27	0.00	-	4.26	-	0.43	3.53
N	59	85	77	-	77	-	85	85

b) Result for best alternative formulation estimates of improved participants

	θ	α_s	β	w	S'	Des. Inv. Cov.	R^2	RMSE
Mean	0.40	0.35	0.31	0.57	-	28.90	0.50	113.39
Median	0.28	0.22	0.15	0.71	-	0.53	0.52	3.45
N	60	85	81	81	-	59	85	85

As explained earlier, w is the parameter of interest for testing the hypothesis that participants are caught up in a reinforcing phantom ordering loop. A w value of 1 means that the participants do not update their expectations about the delivery delay and consider it fixed. On the other hand, a w value of 0 means that when participants are faced with shortages, their expectations about delivery delay is completely floating without being anchored to the normal delivery delay. Mean and median values of w (0.57 and 0.71 respectively) indicate deviation from the rational w value of 1.

We tested the hypothesis that participants place phantom orders (or do shortage or rationing gaming) separately for each participant for which alternative decision rules improve the fit. Hypothesis testing was conducted with likelihood ratio method using SAS statistical software. For 14% of the participants (24 participants out of 171), w parameter was significantly different than 1, suggesting that they were caught up in the reinforcing phantom ordering loops shown in Figure 3. Results for these 24 participants are presented in Table 5. Note that mean and median w estimates are 0.29 and 0.21 for these participants. These values are considerably smaller than the mean and median w estimates (0.57 and 0.71 respectively) of all participants for which the alternative formulations lead to improvement. Analysis of the incoming orders of phantom orderers surprisingly reveals that incoming orders never exceed 4 cases/week for 10 of them. For 17 of them, maximum incoming orders is 12 cases/week. This analysis shows that the variance in the incoming orders of phantom orderers is not a very important driver of panic.

Table 5: Comparison of original estimates and best alternative formulation estimates of phantom orderers.

a) Best alternative formulation estimates

	θ	α_S	β	w	S'	Des. Inv. Cov.	RMSE	R^2
Mean	0.40	0.33	0.23	0.29	-	3.70	147.09	0.57
Median	0.27	0.23	0.10	0.21	-	0.65	3.57	0.63
N	17	24	24	24	-	14	24	24

b) Original formulation estimates

	θ	α_S	β	w	S'	Des. Inv. Cov.	RMSE	R^2
Mean	0.34	0.53	0.14	-	45.86	-	249.85	0.44
Median	0.17	0.38	0.02	-	5.93	-	3.92	0.40
N	17	24	23	-	23	-	24	24

The fact that 14% of the participants placed phantom orders in a setting that disfavors such behavior is a striking result. Econometric results, post-play questionnaire and the anecdotal evidence the authors of this paper have witnessed during their extensive Beer Game facilitation experience suggests that this outcome is in part a result of panic and anxiety experienced by the participants. These type of emotional reactions are not limited to experiments such as the Beer Game, and in fact they are more severe in day-to-day decision making settings of the managers because stakes are much higher and information cues are noisier. Lo and Repin

(2002) measure psychophysiological characteristics of professional securities traders during live trading sessions. They show that even the most experienced traders exhibit significant emotional response to market events. Similar to our findings, they find that the emotional responses are much more dramatic for some participants. Lo et. al. (2005) find that participants with more intense emotional reactions to monetary gains and losses have significantly worse trading performance.

4. Discussion

Experimental conditions presented in this paper eliminate rational reasons for phantom ordering. However, even under these conditions, there is evidence that a significant minority of the participants are caught up in a reinforcing Phantom Ordering loop. Given the experimental conditions, this is a striking finding. Since the participants do not compete against other individuals for getting their orders from their supplier, phantom ordering or shortage gaming is not necessary at all. Phantom ordering might be the rational thing to do in some cases in the real world but not in our experimental setting. Our findings might indicate that people fall back to their default mental models when stressed. There are several examples of panicking and hoarding behavior in real life. Hoarding food during war time, oil during gasoline shortages or hot toys during Christmas season are some examples. Even if phantom ordering is not the right thing to do in this game, participants may have panicked and transferred their experiences from the real world into the game.

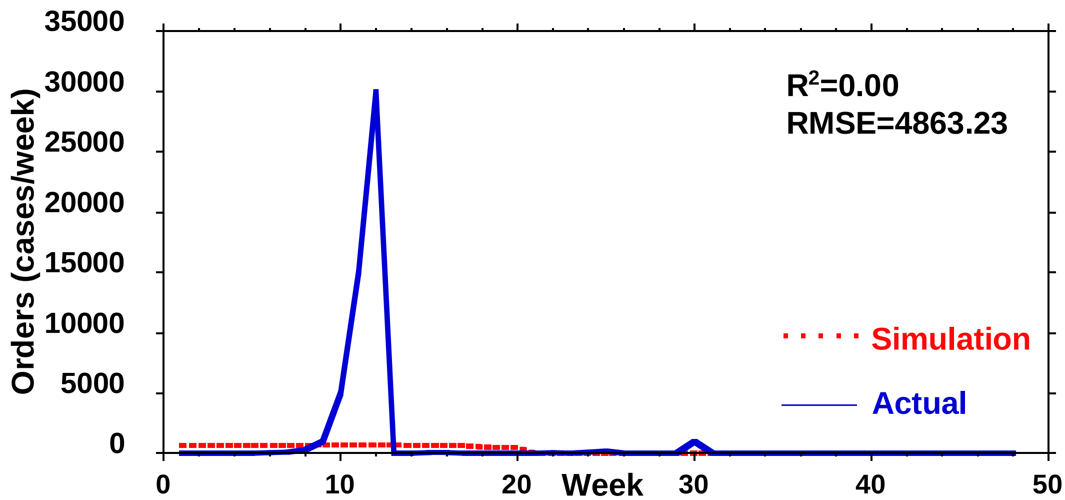
Immediate pressures such as lost sales due to supplier shortage might lead to anxiety and panic, leading to phantom orders even if it'll result in undesirable future outcomes. Neuroeconomics literature suggests that when people need to make a decision involving short term issues, emotional part of the brain is activated and it might dominate the rational part of the brain (Camerer et. al. 2005). If the decision that needs to be made involve only long term issues, rational part of the brain is more likely to be dominant. A person offered the choice between $10 today and $11 tomorrow might be more tempted to choose $10 today whereas it is less likely that the same person will choose the $10 if $10 is offered one year from today and $11 is offered in one year and one day (McClure et. al. 2004). McClure et. al. (2004) present a very clever experiment that tests this hypothesis. Using functional magnetic resonance (fMRI), they scanned the brains of subjects and showed that when subjects need to make a decision involving immediate action, emotional part of the brain is activated along with the rational part of the brain and the tendency to choose immediate/worse action is higher. However, when asked to choose between delayed options that are both long term, emotional part of the brain is not activated and the tendency to choose delayed/better action is higher. This experiment provides evidence that emotions are more likely to be activated under immediate pressures and they might override rational parts of the brain. Shortages put immediate pressure on supply chain managers and cause them to react, possibly as a result of both emotional and rational mechanisms. However, due to time delays the reactions do not relieve the immediate pressure, lead to more panic and reinforce emotional responses.

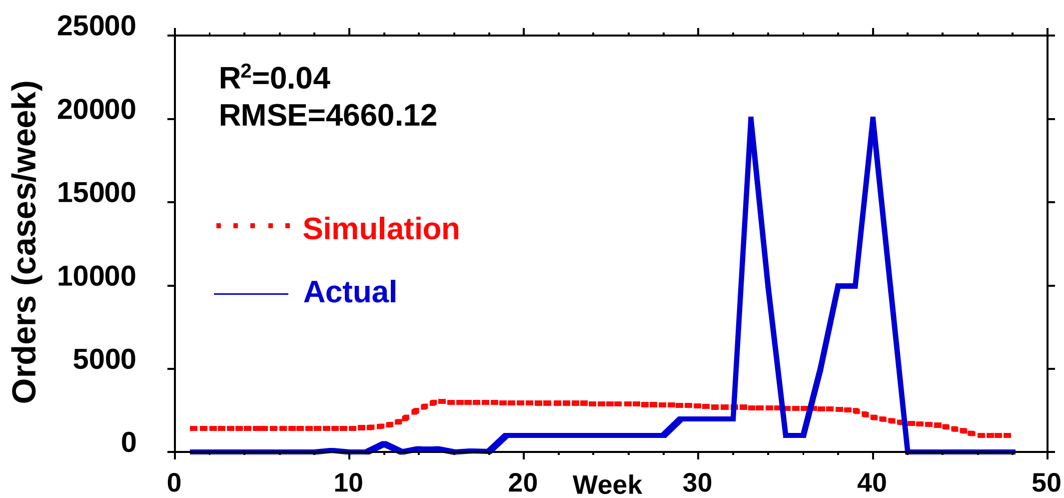
Psychiatry literature suggests that hoarding is one of the symptoms of Obsessive Compulsive Disorder (OCD) (Stein et. al 1999, Maier 2004, Grisham and Barlow 2005). It is shown that lower activity in the dorsal part of the anterior cingulated gyrus of the brain is correlated with hoarding. Functions of that part of the brain include motivation, executive control, focused attention, assigning emotional valence to stimuli, monitoring response to conflict, emotional self-control, problem solving, detecting errors, and selecting responses. The anterior cingulated gyrus also plays a key role in decision making, especially in choosing between multiple conflicting options (Saxena et. al. 2004). It is reported that in some cases patients start hoarding after brain injury or surgery (Hahm et. al. 2001, Eslinger and Damasio 1985). It might be argued that the evidence from OCD patients or patients with brain injury do not represent managers. However, experiments run with normal subjects show that hoarding-relevant photographs provokes these subjects and their brains give reactions similar to that of OCD hoarders (Mataix-Cols et. al 2003). In our experiment, phantom orderers' may have reacted to scarcity with panic and made decisions with less emotional self-control then normal. It is likely that supply chain managers show similar reactions to shortages when they are put on allocation along with other rational reasons. When a customer is put on allocation, there is ambiguity about the real delivery delay and it is documented that normal people do not behave rationally under ambiguity. Ironically, some patients whose brains do not function normally behave closer to the rational predictions of decision theory than normal people under ambiguity (Camerer et. al. 2005).

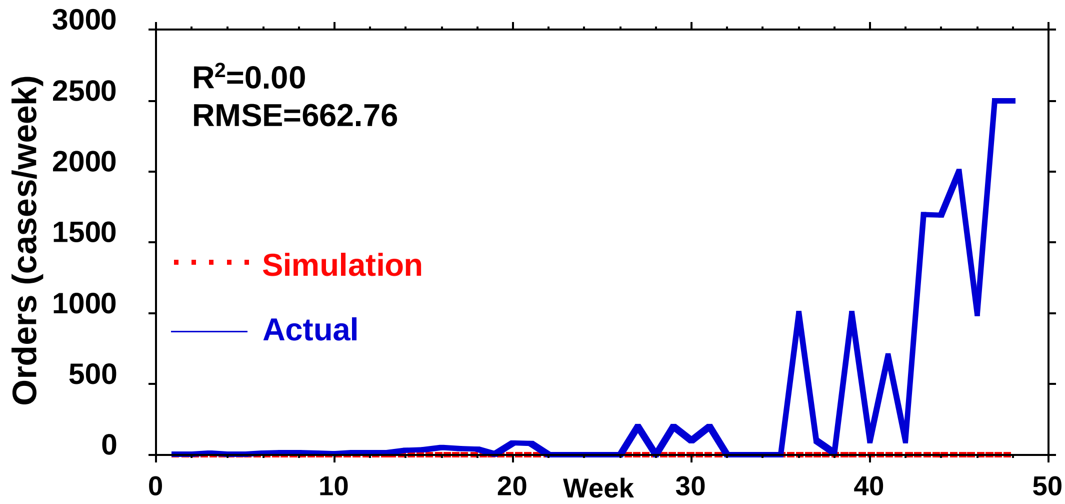
These findings are in line with the view that hoarding is an evolutionary adaptive behavior for humans and animals (Grisham and Barlow 2005) since it was necessary for survival in the early days. In light of our empirical findings and findings of neuroeconomics and psychiatry literature, we speculate that the urge to hoard evolved early in human history as a locally rational response to scarce resources, and that the brain center responsible for the hoarding response is likely to be distinct from the loci of economic decision making. This hypothesis needs to be tested with future research to understand the behavioral reasons of phantom ordering or hoarding and the ways to mitigate it.

Appendix 1

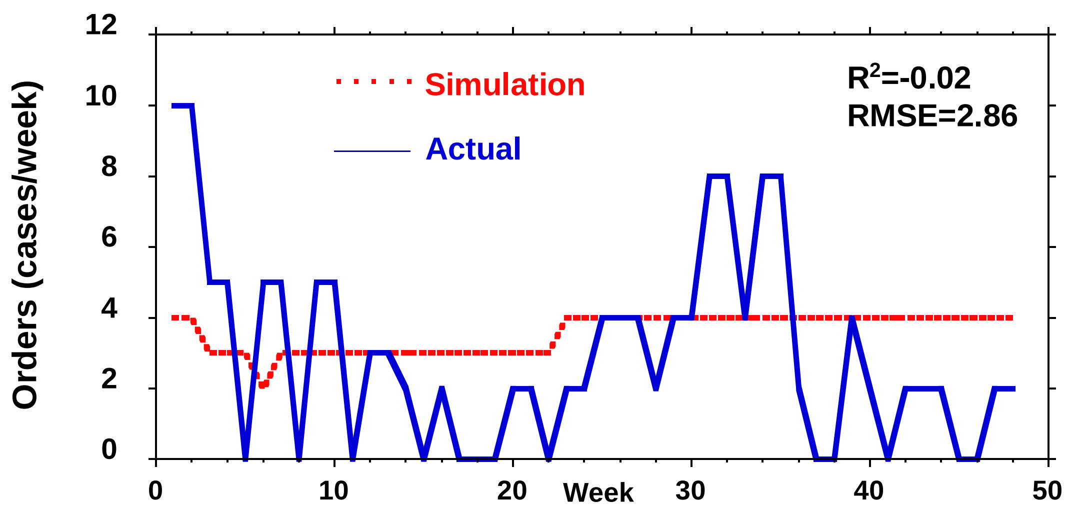
Participants for which the decision rule with fixed desired inventory and desired supply line performs poorly.







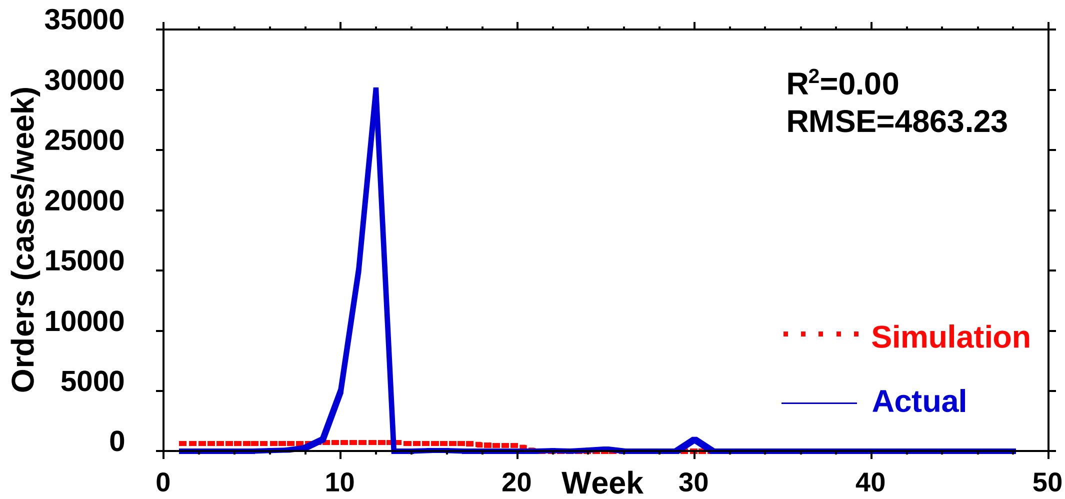
R²=0.00
RMSE=662.76
Simulation
Actual
Orders (cases/week)
3000
2500
2000
1500
1000
500
0
0
10
20
Week
30
40
50

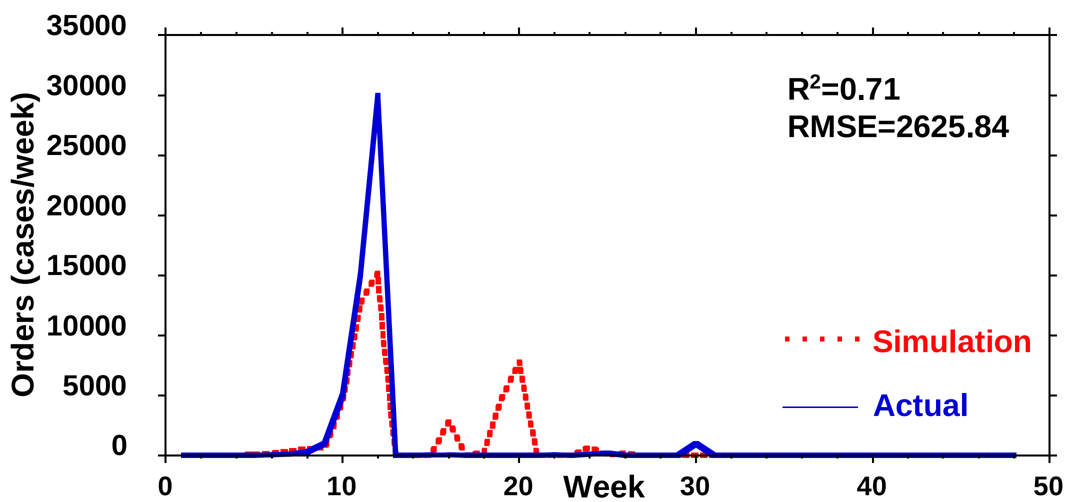


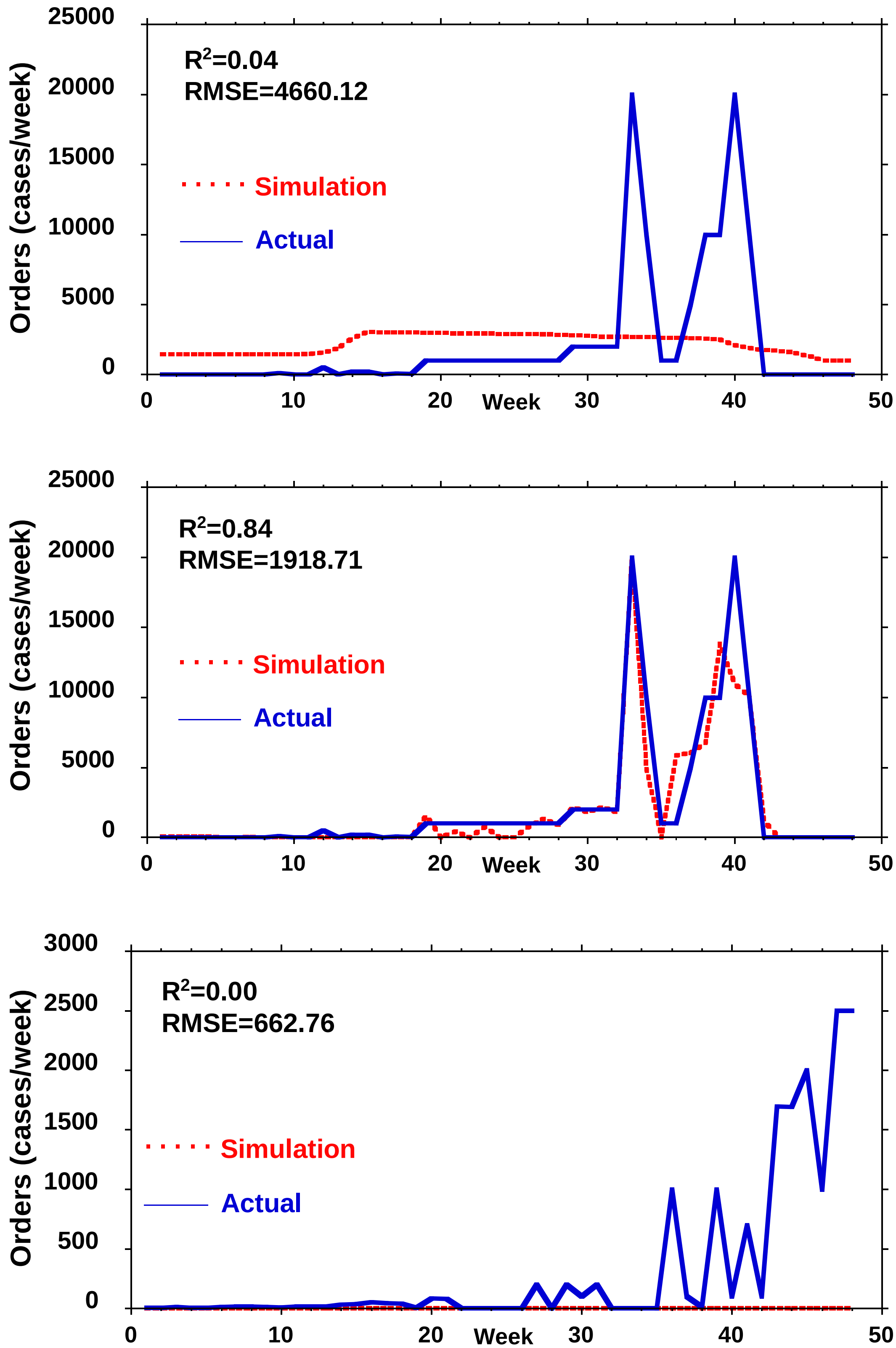
Simulation
Actual
R²=-0.02
RMSE=2.86
Orders (cases/week)
12
10
8
6
4
2
0
0
10
20
Week
30
40
50

Appendix 2

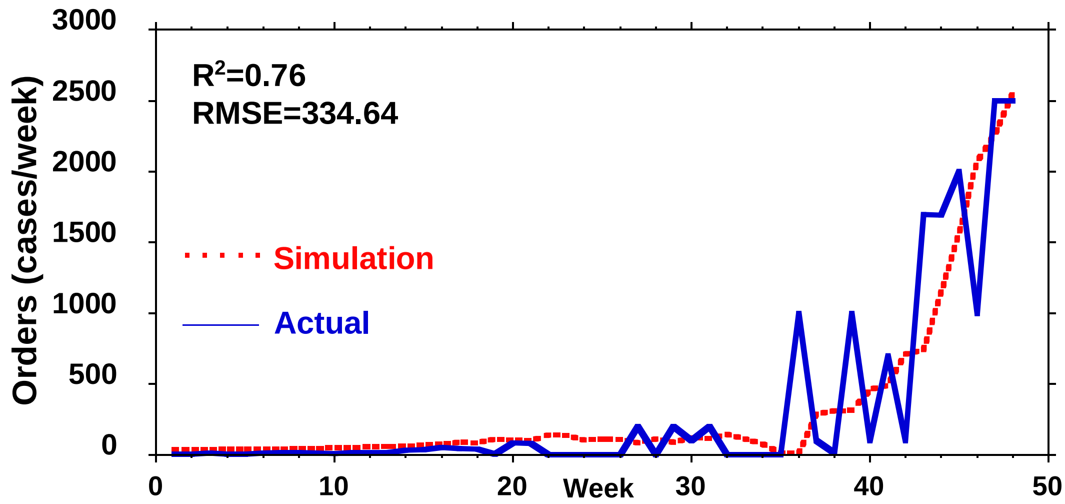
Participants for which relaxing the assumption that desired inventory and desired supply line are fixed leads to considerable improvement in fit.

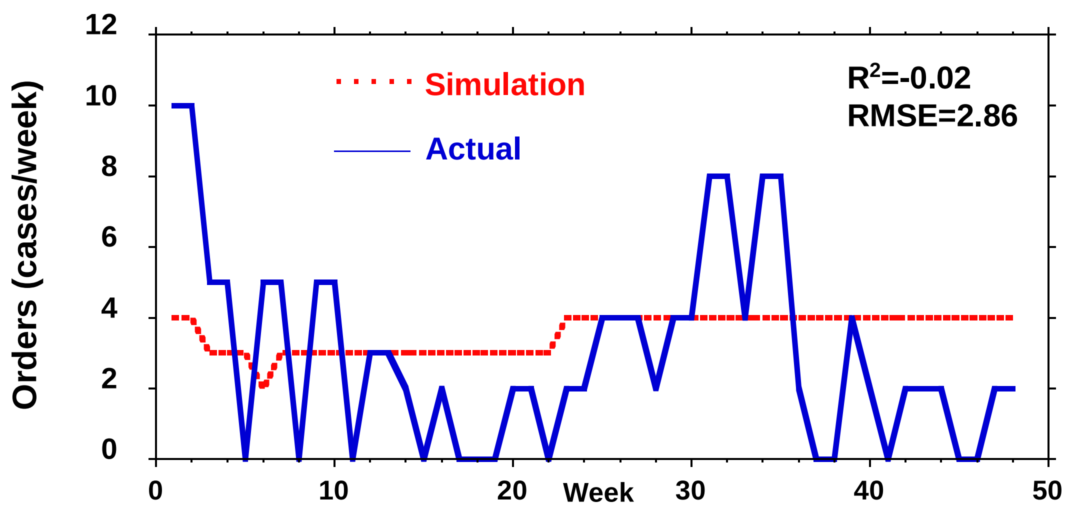


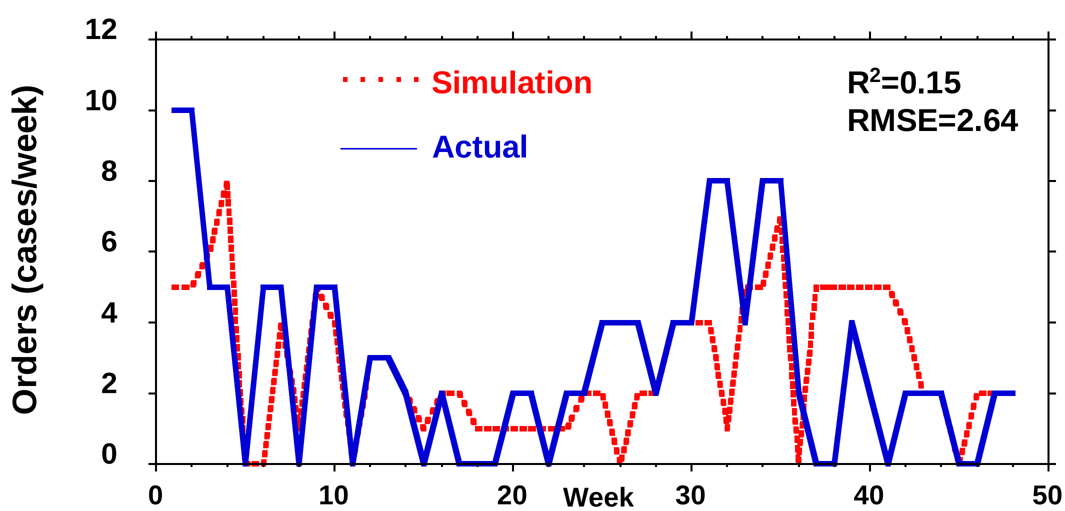


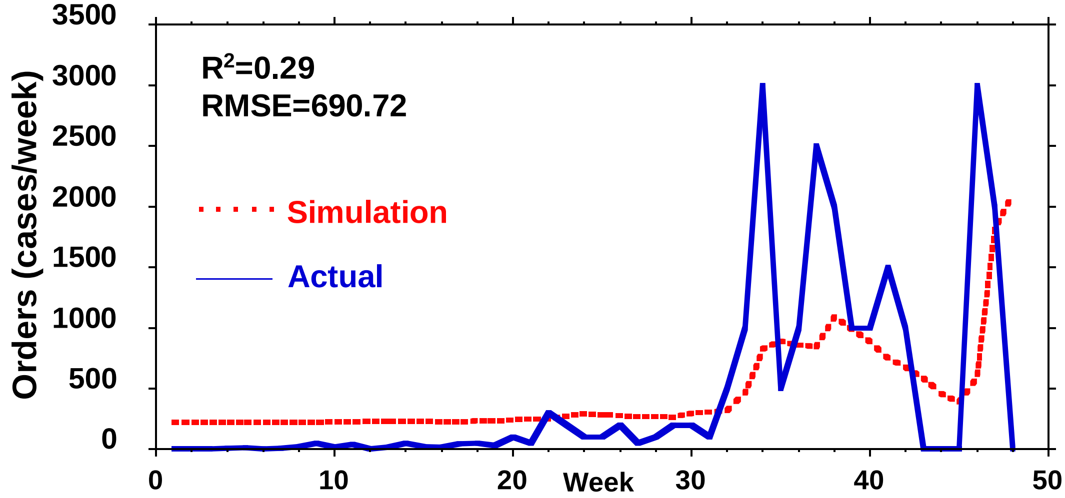


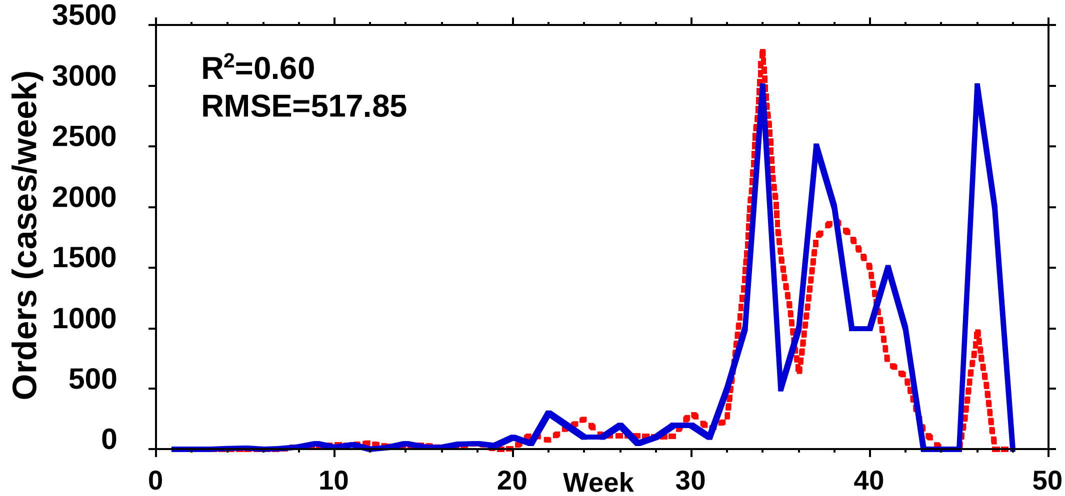
R²=0.04
RMSE=4660.12
Simulation
Actual
Orders (cases/week)
Week
R²=0.84
RMSE=1918.71
Simulation
Actual
Orders (cases/week)
Week
R²=0.00
RMSE=662.76
Simulation
Actual
Orders (cases/week)
Week

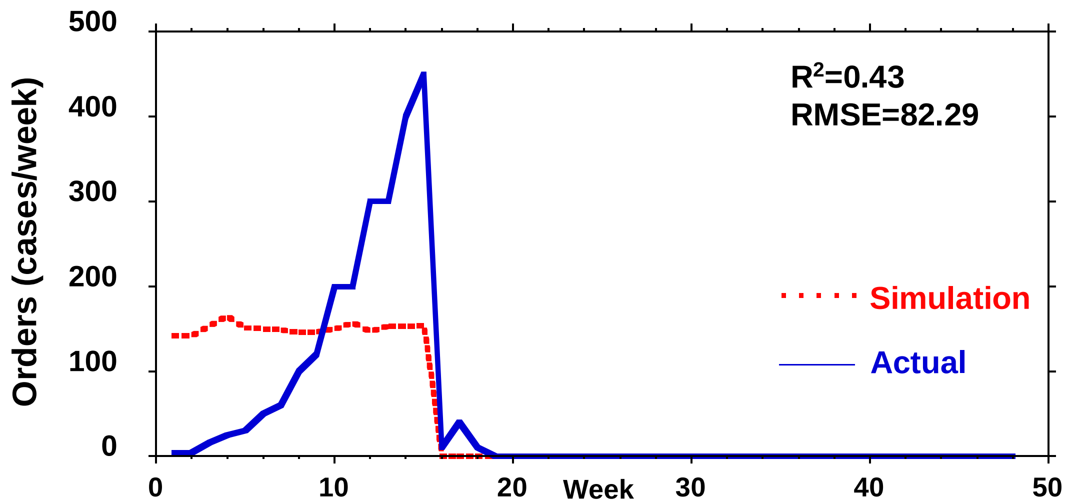

3000
2500
2000
1500
1000
500
0
Orders (cases/week)
R2=0.76
RMSE=334.64
Simulation
Actual
0
10
20
Week
30
40
50

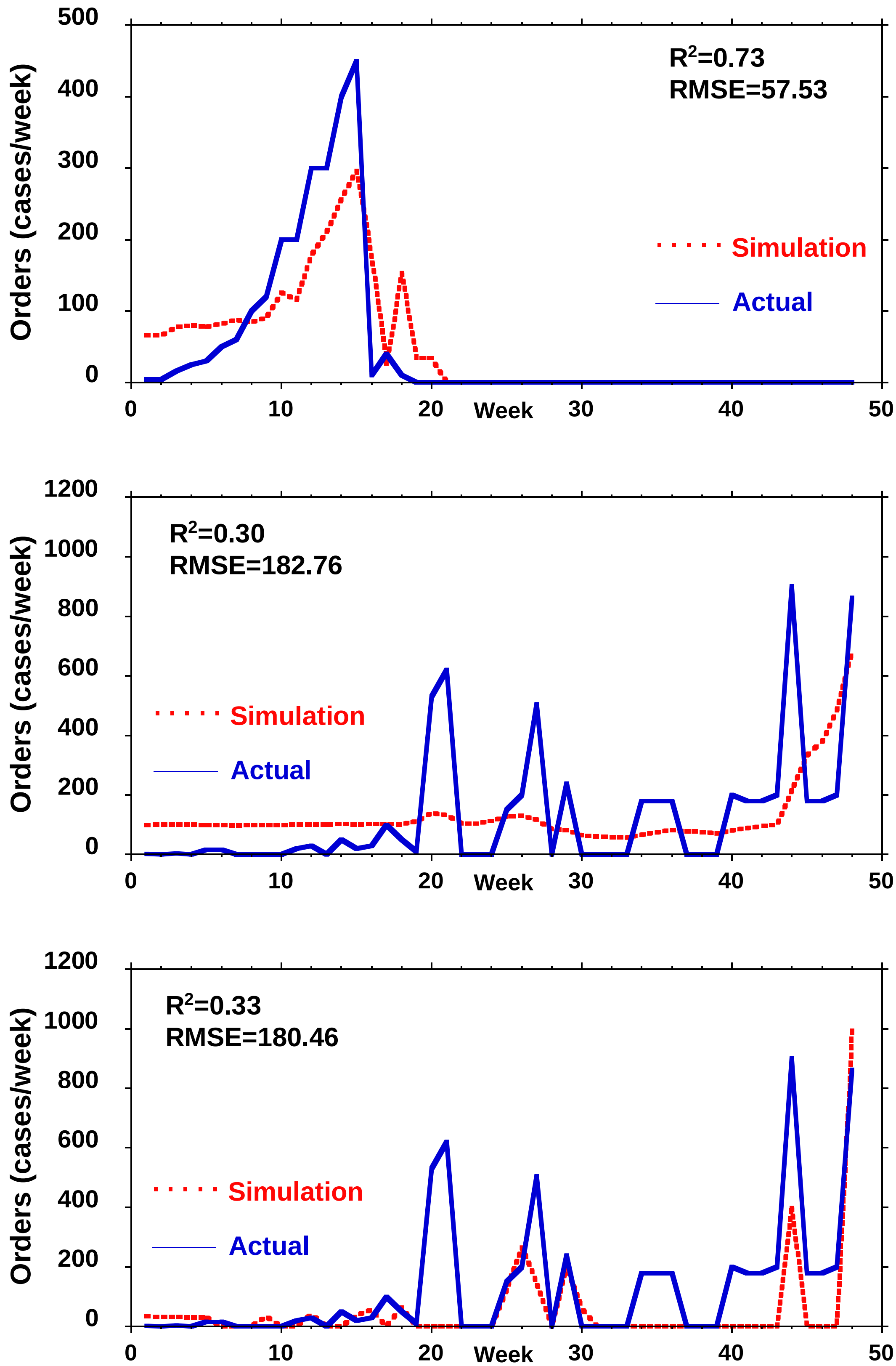

12
10
8
6
4
2
0
Orders (cases/week)
Simulation
Actual
R2=-0.02
RMSE=2.86
0
10
20
Week
30
40
50


12
10
8
6
4
2
0
Orders (cases/week)
Simulation
Actual
R2=0.15
RMSE=2.64
0
10
20
Week
30
40
50

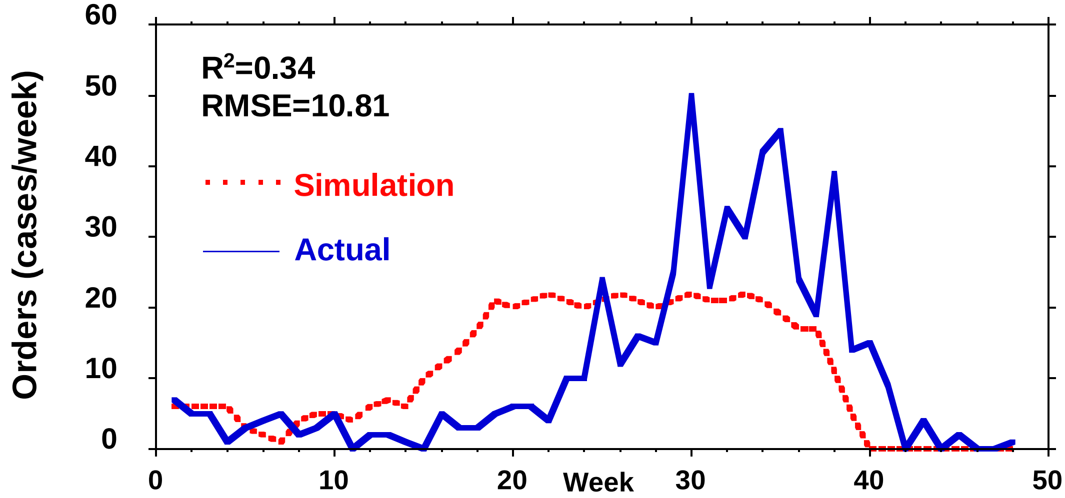

Orders (cases/week)
3500
3000
2500
2000
1500
1000
500
0
R²=0.29
RMSE=690.72
Simulation
Actual
0
10
20
Week
30
40
50

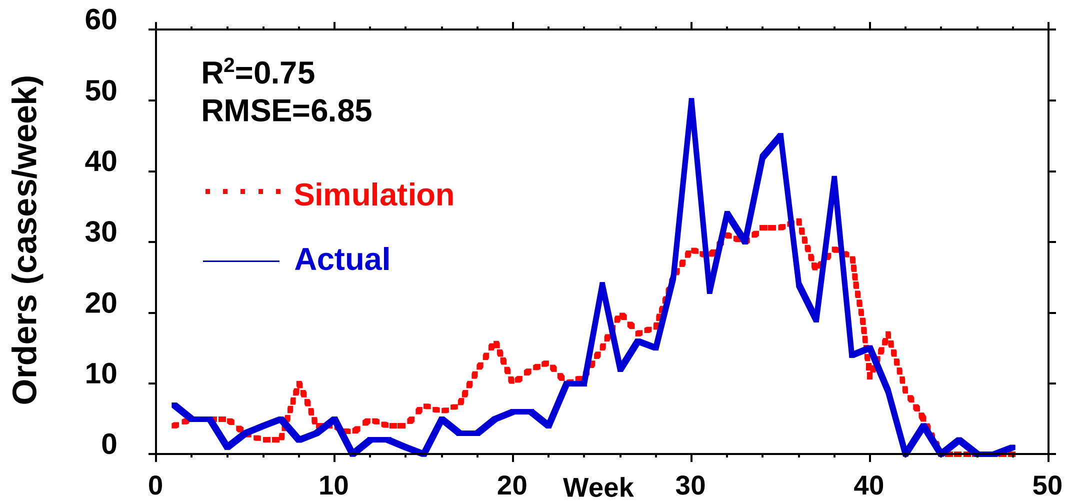

Orders (cases/week)
3500
3000
2500
2000
1500
1000
500
0
R²=0.60
RMSE=517.85
0
10
20
Week
30
40
50


Orders (cases/week)
500
400
300
200
100
0
R²=0.43
RMSE=82.29
Simulation
Actual
0
10
20
Week
30
40
50



Orders (cases/week)
Week
R2=0.73
RMSE=57.53
Simulation
Actual
Orders (cases/week)
Week
R2=0.30
RMSE=182.76
Simulation
Actual
Orders (cases/week)
Week
R2=0.33
RMSE=180.46
Simulation
Actual





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