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Dealer Hoarding, Sales Push and Seed Returns: Characterizing the Interdependency between Dealer Incentives and Salesforce Management

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Abstract

Hybrid seed suppliers experience excessive and costly rates of seed returns from dealers, who order in advance of grower demand realization and may return unsold seeds at the end of the season. Sales representatives know they must carefully gather information on grower demand for seed types and quantities to improve their demand forecast and better position their seeds. However, when pressured to meet sales targets late in the sales cycle, salespeople abandon time-consuming seed positioning to push out dealers' inflated orders. Such push effort leads to excessive returns, generating more inflated orders by dealers the following period and increasing the total sales that agents must achieve to meet their quota, requiring them to push still more seed. Here we develop a formal dynamic model of the interaction of sales effort allocation and dealer hoarding behavior to understand the dynamics of corn seed returns through a model-based field study. Depending on the availability of sales resources, this biased sales effort allocation can generate a self-perpetuating stream of returns. While incentives to dealers solve the dealer hoarding problem, they do not address pressured salespeople's inadequate effort allocation to pushing seeds. Because decreased sales resources and overly-aggressive sales targets increase the pressure faced by salespeople, they also lead to higher seed returns. By understanding the causes of seed returns, our research informs us about the limitations of dealer incentives, shedding light on the important roles of adequate sales resources management and of setting moderate sales targets.

Keywords: Salesforce management; sales resource allocation; dealer hoarding; dealer incentives; sales targets; behavioral modeling; system dynamics.

1. Introduction

The hybrid seed industry experiences excessive and costly rates of seed returns (10% – 30%) from dealers. The demand for hybrid seeds such as corn is highly uncertain, heterogeneous, and deeply influenced by weather and current crop productivity. Year-to-year uncertainty in total corn planted area is high due to changes in prices and supplies (Westcott et al. 2003); planted area uncertainty by region and farm size is even higher. Hence, decisions about aggregate quantity to supply are difficult. Supply is also characterized by long product development and production delays. Suppliers offer hundreds of products, with several new seed hybrids each year. Short and unpredictable product lifecycles lead to rapid turnover of seed hybrids in the catalog. Decisions about what mix of corn-seed hybrids to produce are challenging and must occur months in advance of actual grower demand, leading to common short supply of specific hybrids. Due to uncertain demand and limited supply, dealers place their orders before grower demand is available and inflate them above demand expectations to hedge against shortages of possibly high performing hybrids. Dealer hoarding is a common feature of seed sales in the agribusiness industry.

Aware of dealer hoarding behavior, sales representatives gather information on grower demand for seed types and quantities to improve their demand forecast and better position their seeds. Such positioning effort improves sales forecasts and matches the supply of limited seed hybrids with uncertain demand, reducing seed returns this period. However, as the pressure to meet sales targets builds up late in the sales period, salespeople abandon time-consuming seed positioning to push out dealers' inflated orders and quickly meet their sales targets. Pushing originally inflated orders that do not accurately match to grower demand leads to excessive returns this period. Clearly, the balance between the amounts of seeds positioned and pushed influences the total percentage of seeds returned this period. However, because salespeople must compensate for seed returned this period in the following one, seeds returned this period influence pressure on salespeople to meet sales targets in the next period. Hence, subsequent periods are interdependent. Sales returns in one period influences sales pressure and returns in future periods.

This research provides one example of an adaptation study (as defined by Gino and Pisano 2006) in behavioral operations management (Boudreau et al. 2003, Bendoly et al. 2006). In particular, we describe a field study and develop a formal mathematical model of the interaction of sales effort allocation and dealer hoarding behavior to understand the factors that contribute to the level of seed returns and how the dynamics of seed returns evolve over time. A descriptive field study based on semi-structured interviews and observations provided a number of potential hypotheses for the causes of the problem as well as a list of preferred courses of actions. Based on explicit assumptions elicited from the data and field study, we developed a prescriptive and structured dynamic theory represented in our mathematical model. In particular, we draw on our field work and interviews with managers at the supplier and dealers to develop the physical features (e.g., shipments, returns) of our model. On the behavioral side, we rely on research on cognitive psychology and human decision making (Hogarth 1987, Kahneman et al 1982, Plous 1993, Gersick 1988, Sterman 1989). To capture the interdependency and feedback processes between the physical and behavioral components, we rely on research on system dynamics (Forrester 1961, Morecroft 1985, Sterman 2000, Repenning 2001). Our research suggests that a key factor contributing to excessive seed returns is the unplanned allocation of sales resources to meet revenue quotas late in the sales cycle. In particular, we find that: (1) managerial pressure and sales representatives' efforts to meet quotas coupled with dealer hoarding of scarce products can lead to high return rates, and (2) this mechanism is self-reinforcing.

Sales resource utilization plays a major role determining whether the system can present this self-reinforcing mechanism leading to a high-return equilibrium. Because salespeople must allocate effort between working hard (pushing seeds, i.e., improving performance by requesting dealers to take early delivery of seeds) and working smart (positioning seeds, i.e., generating a better forecast through information gathering on grower demand), a choice to allocate *more* effort to working hard is also a choice to allocate *less* effort to working smart. Task interdependence is particularly important when demand is highly uncertain and salespeople play a crucial role in generating better demand forecasts.

Since demand is highly uncertain in the agribusiness industry, pushing seeds contributes to excessive returns because it *prevents* salespeople from generating better forecasts through positioning.

While a traditional prescription to the problem described here would be to implement adequate incentives for dealers, our analysis shows that the effectiveness of dealer incentives depends on the adequacy of available sales resources. Our analysis shows that stronger penalties for dealer overordering reduce the fraction of returns (for a given salesforce size), however, a smaller salesforce increases the fraction of returns (for a given penalty level). Insufficient sales resources increase the pressure faced by salespeople tilting their time allocation toward pushing more seeds, which ultimately leads to more returns. While incentives to dealers solve the dealer over-ordering problem, they do not address pressured salespeople's inadequate effort allocation to pushing seeds. Hence, both dealer incentives and sales resources must be managed together to ensure adequate system performance. Furthermore, because overly-aggressive sales targets also increase the pressure faced by salespeople, they too can lead to higher seed returns. By understanding the causes of returns, our research informs us about the limitations of dealer incentives, shedding light on the important roles of adequate sales resources management and of setting moderate sales targets.

The paper proceeds as follows. The next two sections present the literature review and describe the field study. Section 4 describes the main assumptions in the model. Section 5 develops a stylized model that captures the essential dynamics of returns in the seed supply chain. Section 6 shows the behavior of the model, proves that the system is characterized by multiple equilibria separated by a tipping point, and explores the interdependence between incentives and sales resources. We conclude with a discussion of our results, its implications, and opportunities for future research.

2. Literature Review

Two streams of literature are relevant to our work: the salesforce compensation and the product return policies literatures. Salesforce compensation schemes attempt to adequately reward salespeople for their efforts (Churchill, Ford and Walker 1981). Because monitoring salespeople's effort is difficult and costly,

however, commissions are frequently used as a motivator due to its direct link between performance and financial rewards. Commissions, or incentive schemes, are widely used in sales environments to reward salespeople for their performance (Eisman 1993, Murphy and Sohi 1995). A number of papers shed light on the design of profit maximizing commission-only compensation schemes (e.g., Farley 1964, Weinberg 1975 and Srinivasan 198 1). While a commission-only scheme can inspire salespeople to work hard, it fails to engage salespeople in activities that are not linked to commissions (Basu et al. 1985, Cravens et al. 1993). Gonik (1978) suggests that good incentive schemes not only compensate salespeople for their effort, so as to motivate them to work hard, but also elicit "good and fresh field information on market potential for planning and control purposes." A compensation scheme that combines a base salary with incentive pay (commissions) addresses the weakness of commission-only plans and accounts for approximately 73% of compensation plans used in practice (Peck 1982). These combined compensation schemes frequently pay commissions only if sales volume exceed a minimum sales threshold with commission levels progressing on a sliding scale until a maximum sales target. The salespeople in our field study received this type of compensation.

Much of the research on the use of sales quotas to motivate sales performance (Davis and Farley1971, Tapiero and Farley1975, Darmon 1979) is based on agency theory (Holmstrong 1979, Grossman and Hart 1983). In agency theory, a principal (firm) relies on an agent (salesperson) to act on the firm's behalf but cannot observe the agent's effort. Mantrala et al. (1994) and Mantrala et al. (1997) design incentive-compatible schemes where quotas can be effectively used to motivate salespeople. Two controlled experiments show that while higher quotas increase effort by salespeople (Winer 1973), sufficiently high quotas decrease effort (Chowdhury1993). Whereas such researchers focus on salespeople's effort, Gaba and Kalra (1999) focus on riskiness to show that high quotas can induce salespeople to engage in high-risk behaviors.

Just like combined compensation schemes, product returns are also common in many different industries. Returns are frequently characterized as the cost of doing business, particularly in uncertain environments. Wood (2001) shows that lenient return policies increase product returns but also consumer

purchase probability, with a positive net sales effect. Pasternack (1985) shows it is suboptimal to offer a return policy giving retailers full credit for all unsold goods. Instead, a policy that offers partial refund for all returned goods can coordinate the supply chain in multi-retailer environments. A number of studies have investigated how to design adequate returns policies as well as control the level of returns (Padmanabhan and Png 1995, 1997; Pasternack 1985; Davis et al. 1995; Tsay 2001).

The literature on return policies also provides several examples of contracts that align retailer incentives with the manufacturers, leading to optimal supply chain profits (see Cachon 2003 for a review). Consider for instance contracts based on rebates. Webster and Weng (2000) find that a return policy that offers rebates for unsold goods at the end of the selling season encourages retailers to place larger orders and can increase manufacturer profits. However, when demand is lower than expected low profits can result from high rebate expenses. When retailer sales effort can influence customer demand, Taylor (2002) finds that a target rebate and returns contract, where the rebate is paid for each unit sold beyond a specified target threshold and unsold units can be returned, coordinates the supply chain. Ferguson, Guide and Souza (2006) propose a target rebate contract to induce the supply chain optimal amount of effort to reduce the number of false failure returns.

3. Field site

Our research rests on data gathered from a three-month in-depth study of a major U.S. supplier of hybrid corn and soybean seeds. Theoretical sampling (Glaser and Strauss 1967) was the motivation for site selection. The seed supplier faced excessive seed returns and provided an amazing opportunity for investigating its causes. Our research goals were twofold: to describe the dynamic behavior observed in the data and to develop theory that helped explain it and lead to improved performance. To develop our general theory of sales resource allocation, we followed standard methods for the development of grounded theory from case study research (Glaser and Strauss 1967, Eisenhardt 1989) and extended it with insights from the literature on judgment and decision making. Fisher (2007) describes a path to empirical research that is similar to the one we followed. Our starting point was descriptive and based on

semi-structured interviews and observations. This phase of the case study unearthed a number of potential hypotheses for the causes of the problem as well as a list of preferred courses of actions, all of which could be investigated later. The final product is a prescriptive and structured dynamic theory based on explicit assumptions elicited from the data.

Our field work included four site visits, weekly conference calls and approximately thirty semi-structured interviews with managers from the supplier and form dealers. Semi-structured interviews allowed us to adapt to different contexts and individuals and to pursue new and unexpected cues suggested by early findings. Most interviewees (80%) were managers at the seed supplier working in different functional areas such as operations, logistics and supply chain management, quarterly initiatives, production planning, demand forecasting, sales and order processing. The remaining interviewees (20%) were managers working at dealers. We followed a joint collection, coding and analysis method for the case study. After site visits and specific interviews, we would revise recorded tapes, summarize field notes and follow up with clarifications or requests for further details. Model assumptions were grounded on the collected data and were verified regularly during weekly conference calls.

Two types of data were gathered and analyzed to ground the development of a system dynamics model of the problem: quantitative and qualitative data. Quantitative data indicated relationships that were initially not salient. For instance, the equation used for dealer hoarding was based both in an actual quote from a dealer, but was also incorporated in a spreadsheet file used by a manager at the seed supplier. Specific data on weekly seed requests by dealers and growers provided context on available information that dealers had when ordering from the supplier. Data on shipment rates, quarterly sales quotas, and fraction of such quotas met by salespeople at different times during the sales season permitted us to evaluate progression toward sales goals, evolving levels of sales pressure and also allowed us to verify the fit of our model behavior with that observed in the field study. Data on net sales and monthly returns could be cross checked against the other data. Qualitative data allowed us to understand the nature of

sales activities, the productivity and probability of returns associated with them, and also heuristics for effort allocation used by salespeople when facing sales pressure.

3.1. Problem description

The major U.S. hybrid seed supplier that we studied experienced 30% of corn seed returns at the time of our intervention (Figure 1a). At that time, the direct costs (e.g., transportation, discards, obsolescence, retesting, reconditioning, repackaging) associated with corn returns at the field site reached 15% of net income. The indirect costs due to excess capacity were also large, since total production was 70% higher than net sales. Seed suppliers often produce in excess of sales and endorse some level of returns, encouraging dealers to overstock seeds to stimulate opportunistic sales or to limit competitors' shelf space. While the benefits associated with additional sales do exist, the costs associated with excessive returns may, at times, far outweigh them.

Figure 1. (a) Percent of corn-seed returns and (b) timing and volume of orders and shipments.

In the seed supply chain, the supplier sells seeds to dealers, who then resell them to growers. Grower demand for hybrid corn seeds is highly uncertain, heterogeneous, and deeply influenced by weather and current crop productivity. Growers place orders with dealers late in the sales season (at the beginning of the first quarter, Q1) and base their orders on hybrids that performed well in the current harvest (in the second half of the fourth quarter, Q4, of the previous year). Supply is characterized by long product development and production delays. Because corn-seed production decisions occur months in

advance of grower demand, short supply of specific hybrids are common. Due to uncertain demand and limited supply, dealers place their orders before grower demand is available and inflate them above demand expectations to hedge against shortages of possibly high performing hybrids (Figure 1b). Shipments from the seed supplier to dealers also take place months in advance of demand.

The seed supplier sales operations start at the beginning of the fourth quarter (Q4) and finish at the end of the first quarter (Q1) of every year. No dynamics contributing to sales or returns take place during Q2 and Q3; hence, these quarters are not modeled explicitly. Dealers place a large fraction of their orders at the beginning of the sales season (October) and returns occur at the end of the sales season (April). For computational convenience and simplicity, we account for orders as occurring at the beginning and returns at the end of each quarter. The quarterly orders and returns representation allows each quarter to be mathematically equivalent and can be interpreted as the fraction of orders and returns that have occurred in that quarter. Figure 2 provides an overview of the stylized seed sales process.
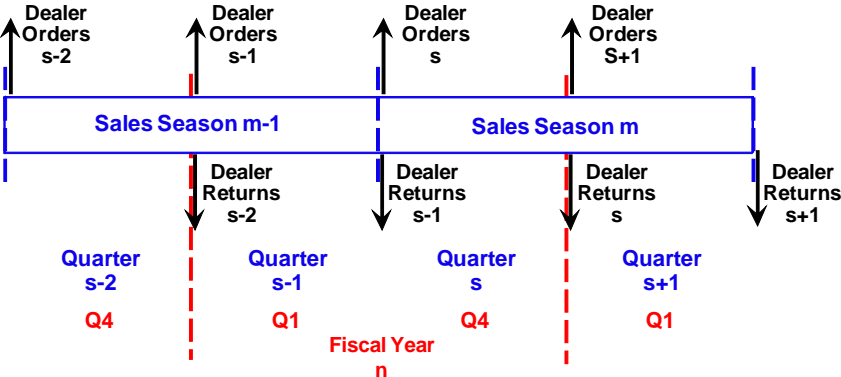

Figure 2. Overview of seed sales process.

4. Model Assumptions

Five main assumptions are central to the dynamics of our model. The first describes the heuristic used by dealers to determine their order level. The second and third assumptions explain the productivity and probability of returns associated with sales activities available to salespeople. The fourth describes how sales pressure influences sales people effort allocation between different activities. The last assumption explains the sources of pressure that salespeople bear.

4.1. Dealer hoarding behavior

The first key assumption captures dealers' hoarding behavior. Dealers place large orders early to hedge

against the possibility of shortages. As one seed dealer expressed:

> "We base our orders on last year's sales and typically increase by 10-20% … [placing] 50% of
> total orders early in the season… We would order more than that, if we knew that supplies were
> short… If my sales rep would tell me that a certain variety is on short supply, I would order as
> much as I could, or as much as my rep would allow."

Dealers' initial orders are largely determined by the fraction of seeds returned the previous year.

A large fraction of returns in one year leads to large expected returns in the following, causing dealers to

inflate their orders to compensate for them. For instance, suppose a dealer orders the exact number of

units to meet grower demand (*G*). Because of unpredictable weather conditions and imperfect knowledge

of grower preferences, the dealer sells only a fraction of their order, (*1-r*)*G*, returning the rest (*rG*). The

following quarter, to be able to sell *G* units and meet grower demand, dealers must order *G/(1-r)*. For

simplicity we assume that dealers have a good estimate of the underlying aggregate grower demand (*G*);

poor estimates of grower demand would further amplify dealer hoarding and would strengthen the results

reported here.

$$O_S = \frac{G}{\left(1 - r_{S-1}\right)} \tag{1}$$

where r_{S-1} is the amount of returns, *r*, in the previous quarter, *S-1*.

4.2. Sales activities

During the sales season, salespeople must perform two (very different) types of tasks: *position* seeds with

dealers or *push* seeds to them. Positioning means salespeople gather information on grower demand,

before it is realized. Through field trips and interviews with growers and dealers, salespeople seek to

understand which hybrids used in the previous season were high performing (similar hybrids will likely

be in high demand this season); explore growers' intentions to maintain planted areas or to rotate between

crops; review the previous season's hot selling hybrids; and survey dealers' intentions to gain market

share. Positioning seeds is a time intensive task. However, salespeople's positioning effort leads to an

improved sales forecast, more effectively matching the supply with the highly heterogeneous demand. In contrast, pushing seeds to dealers does not improve the order forecast. Pushing seeds is comparatively quick and involves making phone calls to request dealers to take delivery of early inflated orders placed. By pushing seeds, salespeople increase their revenue contribution, rapidly closing the gap to their quarterly revenue targets.

4.2.1. Productivity of sales activities

While both activities consume the same resource, salespeople's hours (H) averaging about 50 hours/week, our interviews with sales managers suggest that the time required to position (T_A) a certain quantity of seeds is substantially higher than the time necessary to push (T_B) the same amount. The time to position a load (L) of 40 bags of corn at dealers is on average 5 hours, whereas the time to push the same amount is on average 1 hour. Average times to position and push corn seeds were estimated using one year of seed shipment data and interviews with sales managers that identified periods where seeds were positioned or pushed. Assuming a constant number of salespeople in the workforce (W), we obtain the positioning rate (A) and pushing rate (B), in number of bags of corn/week, from the ratio of the total number of salespeople's hours to the time to place (position or push) them at dealers.

$$A = \frac{W \cdot H \cdot L}{T_A} \text{ and } B = \frac{W \cdot H \cdot L}{T_B} \tag{2}$$

Since the time required to position (T_A) is much greater than the time required to push (T_B) the same amount of seeds, the positioning rate (A) is much slower than the pushing rate (B), i.e., because $T_A \gg T_B$ it follows that $A \ll B$.

4.2.2. Probability of returns due to sales activities

An important aspect of both sales activities is the impact they have on the probability of this period's returns. Since salespeople's positioning effort results in a better forecast of grower demand, it allows them to better align supply availability with specific dealers' needs, thereby reducing the probability of returns. In contrast, since salespeople's pushing effort results in shipping inflated dealers' orders, it does

not align supply to demand leading to a higher probability of returns. We assume a fixed low probability of returns, P_L, when salespeople position seeds and a high probability of returns, P_L+P_H, when salespeople push them. P_L is the probability of returns that cannot be avoided by gathering demand information through positioning; and, P_H is the probability of returns that can.

4.3. Sales effort allocation

The fourth assumption specifies the mechanism by which salespeople allocate their time between positioning and pushing seeds. First, for simplicity, we assume that salespeople do not shirk, so the total amount of salespeople's hours available for positioning and pushing is fixed at 50 hours/week. While the goal-gradient hypothesis – originally proposed by Hull (1934) and recently revisited by Kivetz, Urminsky, and Zheng (2006) – suggests that proximity to the goal (deadline) leads to a stronger tendency to approach the goal (more salespeople's hours/week), relaxing the fixed effort assumption would intensify the effectiveness of push efforts and strengthen the results presented here. The *a fortiori* assumption of fixed effort provides a more stringent test of our theory.

The formulation for salespeople's allocation of effort between positioning and pushing seeds is based on our field study and also on research on motivation (Steel and König 2006) and work teams (Gersick 1988, Gersick and Hackman 1990). Our interviews suggest that salespeople initially devote time to positioning activities, but eventually they shift to pushing activities. According to a sales representative:

> "We start out really trying to load toward true grower demand. Everybody makes an honest effort of positioning seeds. But when it gets down to crunch time … you are just shipping what you can get, where you can get it, and when you can get it."

We aggregate salespeople, capturing their mean response over the distribution of possible response strengths. While the intensity of individual responses follow a distribution, our interviews suggest that salespeople respond similarly to the same stimuli. All salespeople interviewed characterized that they faced a "crunch time" during which they pushed seeds, expediting dealer orders. We implement the effort allocation shift from positioning to pushing activities as taking place when pressure to meet

revenues (p) is greater than a pressure threshold (p_T). Combining the mechanism by which salespeople allocate effort between positioning and pushing activities and their associated return probabilities, we can determine the overall probability of returns. When sales pressure to meet quarterly goals (p) is below the threshold (p_T), salespeople position seeds with the minimum unavoidable probability of returns (P_L). When sales pressure exceeds the threshold (p_T), salespeople push seeds with the maximum probability of returns (P_L+P_H). The *Overall Probability of Returns* (P_W) is:

$$P_W = \alpha P_L + (1 - \alpha)(P_L + P_H) \quad \text{and} \quad \alpha = \begin{cases} 1, & \text{if } p < p_T \\ 0, & \text{if } p \geq p_T \end{cases} \tag{3}$$

where α is the fraction of resources allocated to positioning seeds.

This formulation is supported by our field work which suggests, as illustrated by the quote above, that the switch from positioning to pushing takes place quickly. This sharp switch happens as salespeople realize that there are only few weeks left in the quarter to meet the revenue quota. This sharp reversal between activities is consistent with a number of theories of motivation (Steel and König 2006). Also, research on work teams (Gersick 1988, Gersick and Hackman 1990) suggests that the behavior of groups on tasks tends to shift to greater focus on completing the task about halfway through the time allotted. Similar results are obtained if the shift from positioning to pushing activities takes place linearly over time (for details see the derivation in Appendix 1).

4.4. Sales pressure

We model the pressure to meet quarterly revenue goals (p) as the fractional revenue required to meet the quota relative to the fraction amount of time remaining to do so. Specifically, the pressure is the ratio of the revenue gap fraction (*RG*) to the time remaining fraction (*TG*). The proposed pressure formulation leads to a pattern of behavior that is consistent with the explanations obtained from the value function of Prospect Theory (Kahneman and Tversky 1979) for empirical results in the goal literature on effort (Heath, Larrick and Wu 1999).

$$p_S(t) = \frac{RG_S(t)}{TG_S(t)} \qquad (4)$$

where quarters are discrete and characterized by the subscript *S*; time within a quarter is continuous and indexed by *t*; and, $p_S(t)$ is the pressure in quarter *s* at time *t*.

The fractional revenue gap measures the fraction of the original distance remaining to the revenue goal. Hanssens and Levien (1983) and Carroll et al. (1985) have used a similar construct to measure recruiter pressure in navy enlistment programs. More recently, Kivetz, Urminsky, and Zheng (2006) named it the goal-distance model and used it to describe the rate at which customers allocate effort as a function of the fractional distance remaining to the goal. Here, the fractional revenue gap (*RG*) is modeled as the difference between the target revenue (R^*) plus lost revenues from previous quarter returns (RL_{S-1}) and current accumulated gross revenues (GR_S), normalized by the target revenue (R^*) and last quarter lost revenues (RL_{S-1}). That is, to meet the quota this period the salesperson must achieve revenues of R^* plus enough revenues to cover the cost of returns from last period.

$$RG_S(t) = \frac{\left(R_S^* + RL_{S-1}\right) - GR_S(t)}{\left(R_S^* + RL_{S-1}\right)} \qquad (5)$$

While the time remaining to make a decision is not traditionally incorporated in many marketing models, research applying regret theory to model the impact of coupon expiration date on consumer behavior suggests that high redemption rates take place just prior to the expiration date (Inman and McAlister 1994). In addition, time remaining is a major component of hyperbolic discounting theory, a theory that helps to describe choice behavior over time (Ainsle and Haslam 1992). The fractional time remaining in the quarter (*TG*) is given by the ratio of the time remaining to the total time available in the quarter, *T* (13 weeks), where the time remaining is given by the total time in the quarter (*T*) minus the time elapsed (*t*).

$$TG_S(t) = \frac{T-t}{T} \qquad (6)$$

As time to meet revenue quotas elapses, the fractional time remaining approaches zero and salespeople pressure rocket toward infinitum. It is possible to improve on the formulation above by adding a constant, τ, characterizing the minimum fractional time required to complete the simplest task. This more robust formulation is consistent with Mazur (1987), but unnecessary here. In our hybrid discrete-quarters continuous-time model, model parameters are reinitialized at the beginning/end of each quarter and the maximum sales pressure is inversely proportional to the time step of integration.

5. Model Structure

Figure 3 provides a more detailed view of the central structure in a system dynamics model of the corn-seed supply chain. Stocks, represented by rectangles, correspond to accumulations of seeds. Stocks are mathematically equivalent to integrals. Flows, represented by arrows with valve symbols, correspond to actions, such as shipments. Flows are mathematically equivalent to derivatives. Solid arrows capture the influence of other variables on the flows.
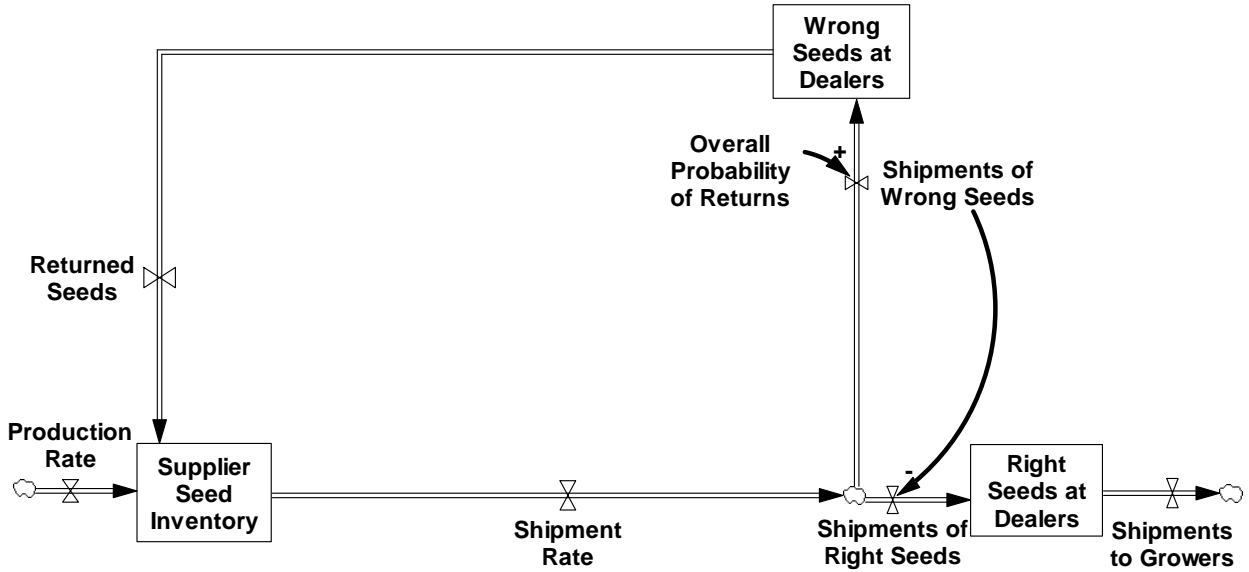

Figure 3. Stock-and-flow diagram for seed supplier shipments.

At the beginning of each quarter, the *Production Rate* and *Returned Seeds* from the previous quarter replenish the stock of *Seed Supplier Inventory*. Sales effort to position or push seeds determines

the *Shipment Rate*, according to the positioning and pushing rates given by equation 2. Shipments decrease the supplier inventory. The probability of having the "right" (or "wrong") seeds, i.e., seeds with (or without) corresponding grower demand, reaching dealers follows equation (3) and depends on sales effort allocation to positioning or pushing seeds. The quantity of *Wrong Seeds at Dealers* accumulates over the quarter at a rate given by the product of the *Shipment Rate* and the *Overall Probability of Returns* (P_W). Wrong seeds accumulated at dealers return to the supplier inventory at the end of the quarter and are accounted as *Lost Revenues from Returns*. The quantity of *Right Seeds at Dealers* accumulates over the quarter at a rate given by the *Shipment Rate* minus *Shipments of Wrong Seeds*. Right seeds accumulated at dealers are shipped to growers.
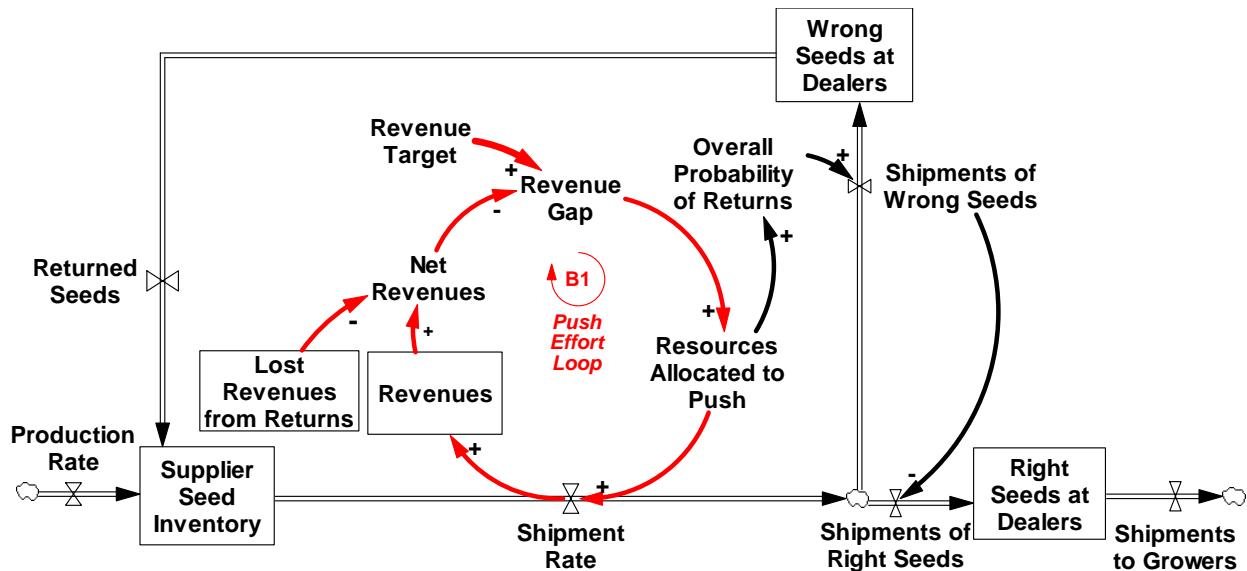

Figure 4. Push effort balancing feedback loop.

Figure 4 incorporates an important feedback loop capturing salespeople's heuristic for pushing seeds. The push effort loop (B1) is a balancing (or negative) feedback mechanism that regulates the revenue gap by adjusting the amount of effort allocated to pushing seeds. A large discrepancy (*Revenue Gap*) between the *Revenue Target* and *Net Revenues* leads to high pressure to meet quarterly revenue goals. While sales pressure is below the threshold, salespeople allocate resources to positioning seeds, shipping seeds to dealers with the positioning rate, *A*, and a probability of shipping wrong seeds, P_L.

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However, once sales pressure rises above the threshold, salespeople start pushing seeds, shipping seeds to dealers with the faster pushing rate, *B*, and a higher probability of shipping wrong seeds, P_L+P_H. As salespeople push seeds, they accumulate *Revenues* more rapidly in the quarter, closing the revenue gap and easing the pressure to meet quarterly revenue quotas.
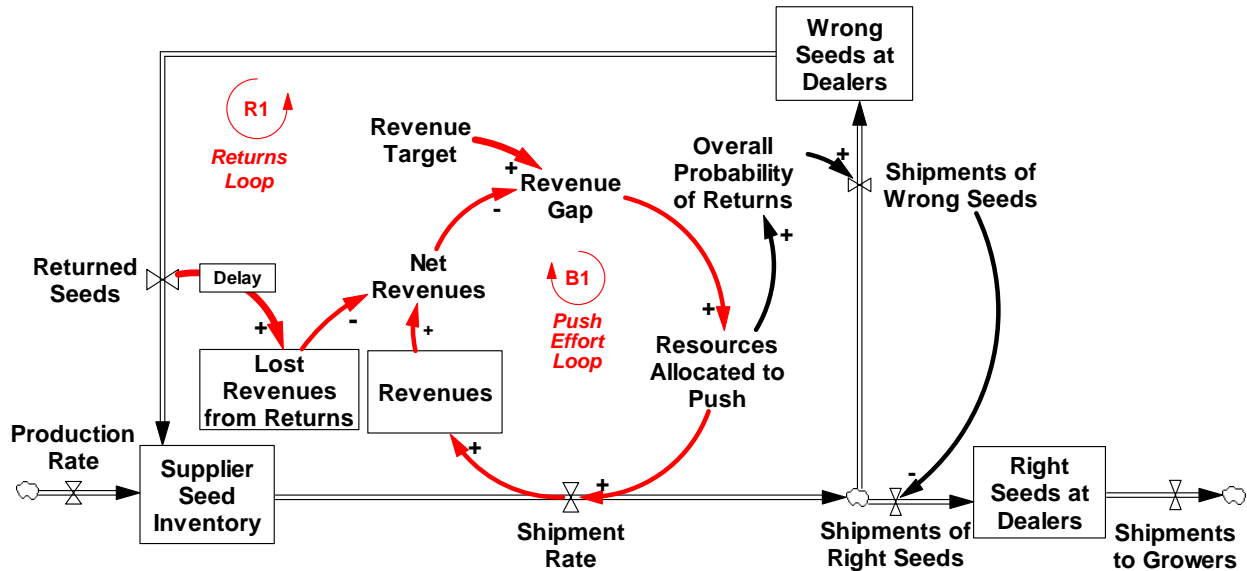

Figure 5. Returns reinforcing feedback loop.

Figure 5 incorporates a reinforcing (or positive) feedback mechanism, the returns loop (R1), capturing the impact of seed returns in the system. The reinforcing loop can operate in a vicious or virtuous way. If sales resources are sufficient to position a large quantity of seeds, pressure to meet revenue goals remains below the pressure threshold for most of the quarter, resulting in a small amount of seeds pushed and consequently a small amount of returns. The following quarter, dealers do not need to inflate orders as much and sales resource requirements are even lower, requiring salespeople to push an even smaller amount of seeds, leading to even lower returns. As described here, the reinforcing loop behaves in a virtuous way. In contrast, if sales resources are insufficient to position a sufficiently large quantity of seeds, pressure to meet revenues goals will mount. After pressure increases above the threshold, salespeople will push more seeds, leading to a higher probability of shipping seeds to dealers with inadequate grower demand and resulting into a large fraction of returns. Higher returns result in lost

revenues; increase the following quarter's revenue gap and the pressure on salespeople; and raise resource requirements for the following quarter, compelling salespeople to push even more seeds. The loop works in a vicious way, leading to high returns and poor salesforce performance.

Perfectly rational salespeople (or firm managers) would not allow such a vicious cycle to occur. But properly assessing the costs and benefits of pushing and seeing how pushing today hurts revenue tomorrow is difficult. The benefits of pushing seeds are recognized immediately – salespeople get rewarded (they receive a cash bonus) for meeting the quarterly revenue target, but the costs associated with returns occur only much later. Also, while the benefits of pushing seeds are financial, the costs of returns to salespeople are not. When returns occur at the end of the quarter, the associated lost revenues are accounted for in the following quarter, increasing the revenue gap, raising pressure to meet the quarterly goals and compelling salespeople to push even more seeds.

6. Model Behavior and Analysis

Table 1 presents the base case parameters for the model. Since the important activity with respect to seed sales occur in the first and fourth quarters, our model, without loss of generality, captures two quarters in each simulated year (Q4 and Q1). Base case results are shown in Figures 6 and 7. Without an exogenous (external) shock, system behavior in the base case scenario is the same in each quarter. To explore the internal dynamics of the modeled system, we study its operation without external random shocks; instead exploring how a single perturbation may trigger an endogenous increase in returns. We discard the first five years of each simulation to avoid initial transient behavior.

TABLE 1 – BASE CASE PARAMETERS

Parameter	Definition	Value	Units
G	Grower demand	1,800,000	Seed bags
T_A	Time to position seeds	5	hours/40 seed bags
T_B	Time to push seeds	1	hours/40 seed bags
W	Number of salespeople in workforce	420	salespeople
H	Number of work hours per week	50	hours/week
T	Number of weeks in quarter	13	weeks
P_L	Probability of returns when salespeople position seeds	0.1	-
P_L+P_H	Probability of returns when salespeople push seeds	0.6	-

Note: Base case parameters are motivated by values obtained through interviews with the seed supplier. Parameter values for P_L and P_H are difficult to assess for the real supplier. Here, their choice is arbitrary. The behavior of the system would be similar for a large range of values (e.g., higher P_L and lower P_H).

6.1. Base case

Early in the quarter salespeople have plenty of time to sell, pressure to meet the revenue target is low (Figure 6a) and salespeople allocate effort to positioning seeds (Figure 6b). Shipments to dealers take place at the positioning rate, *A*. Since the probability of shipping seeds without corresponding grower demand is small, P_L, the amount of "right" seeds at dealers, increases rapidly (Figure 7a). If sales resources are insufficient to position all seeds and meet the revenue targets, pressure increases as the end of the quarter approaches (Figure 6a).
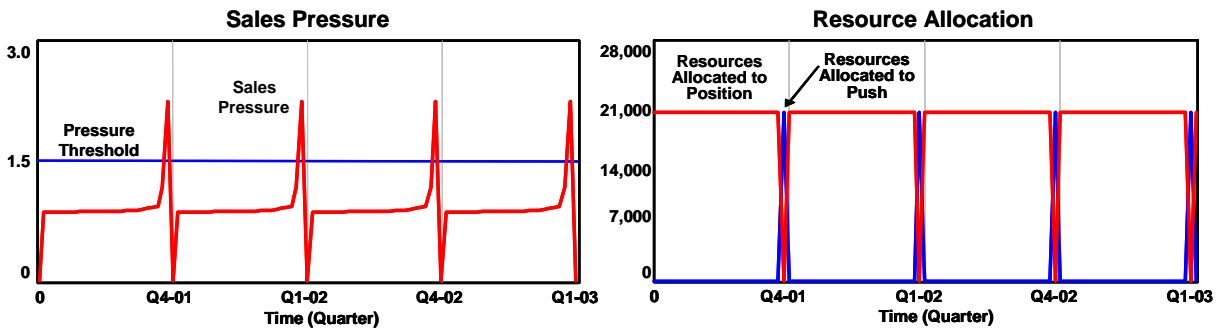

Figure 6. (a) Sales pressure and (b) resource allocation.

When the pressure reaches a threshold, salespeople shift resource allocation from positioning to pushing seeds (Figure 6b). During these high-pressure "crunch" periods, seed shipments take place at the much faster pushing rate, *B*, and the higher probability of returns, P_L+P_H (Figure 7a). The increased

shipment of wrong seeds accumulates over time, leading to higher returns to the seed supplier at the end
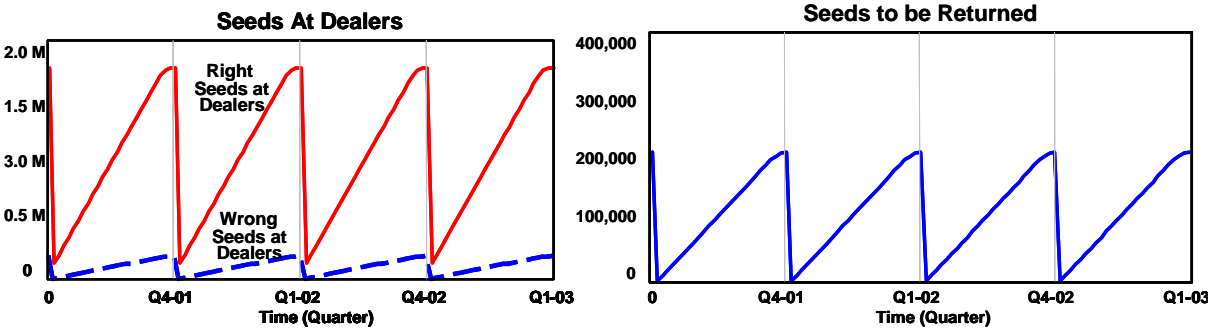
of the quarter (Figure 7b).

Figure 7. (a) Seed stocks at different dealers and (b) shipments to wrong dealers.

In the base case, the simulated supplier allocates most resources to positioning seeds, and pushes

only a modest amount of wrong seeds to dealers, so total returns are relatively small. While dealers'

orders in the following quarter compensate for the fraction of seeds returned in the previous one, the small

amount of returns allows salespeople to allocate most of their time to positioning seeds, thereby limiting

future returns. Contrasting the base case behavior with observations from the field study, we note that

seed stocks accumulated at regional dealers follow closely the pattern in the model. However, sales

pressure increases earlier in the quarter, a significant amount of sales effort is devoted to pushing seeds,

and the fraction of returns is considerably higher.

6.2. Demand shocks

Given the desired mode of operation in the base case, it is important to explore whether the modeled

system can generate the excessive returns observed in the seed supplier as well as what factors may

contribute to it. Two simulation experiments provide insight into these questions. In these simulations, we

temporarily increase grower demand (and sales quotas) in the first quarter, by 5 percent and 10 percent

respectively, returning them to base case levels during the remaining quarters. This transient increase in

demand might arise due to a rise in the price growers can get for their corn or an increase in government

subsidies.

With fixed sales resources and increased dealer orders, salespeople are unable to position all seeds and must increase their dependence on pushing seeds to dealers. In both simulations, following the increase in grower demand, the fraction of time salespeople allocate to positioning falls (Figure 8a). As more seeds are pushed, the probability of sending the wrong seeds increases, leading to more returns (Figure 8b). In the case of the 5% increase, the fraction of time allocated to positioning begins to recover and the fraction of seeds returned falls after a while. Though the demand shock increases the fraction of returns temporarily, the system is able to recover and goes back to the desired operation mode where salespeople position their seeds most of the time.
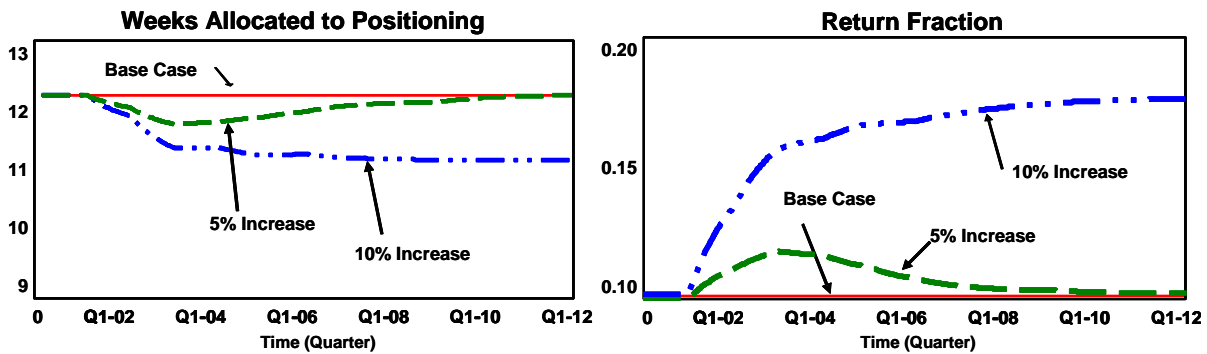

Figure 8. (a) Weeks allocated to positioning and (b) return fraction.

The behavior resulting from a 10% increase in demand, however, is quite different. Here, the fraction of time allocated to positioning does not recover after grower demand returns to normal levels. As more seeds are pushed to dealers, a larger fraction is returned, requiring even more pushing the following quarter. Following the transient increase in demand, the system settles in a new operation mode, in which a large fraction of salespeople's effort is allocated to pushing seeds and the fraction of seeds returned is permanently high. In this case, the demand shock is sufficient to bring the system to a high-return operation mode.

6.3. Phase plot analysis

To understand why different size shocks generate such divergent behavior, we follow an analysis procedure developed by Repenning (2001). First, we reduce the high order nonlinear structure of the

system to a one-dimensional map, by studying the system dynamics *between* quarters. Since dealer

orders in a quarter depend on seeds returned in the previous quarter, and since the system is integrable, we

can capture the dynamics of returns as a discrete time map in which returns this quarter, r_S, are a function

of returns last quarter, r_{S-1}, that is, $r_S = f(r_{S-1})$; see, e.g., Ott (1993). Second, we use the map to characterize

the conditions required for the different operating modes of the system to emerge. Resource availability

and the positioning and pushing rates in the sales organization play an important role in determining the

operating mode of the system. To derive the map, we begin with the determination of returns as a

function of salesforce effort (see appendix 1 for details on this derivation):

$$r_S = P_L + P_H Max\left(0, \frac{B(T_F - t_C)}{At_C + B(T_F - t_C)}\right) \tag{7}$$

where A is the positioning rate, B is the pushing rate, t_C is the critical time when salespeople shift from

positioning to pushing (associated with the pressure threshold, p_T), and T_F is the time that shipments end

(which may occur before the end of the quarter, T.) If $T_F = T$, the supplier may or may not be able to ship

all dealer orders. Note that pushing seeds has the positive effect of allowing the supplier to ship a greater

fraction of dealer orders. The additional amount of seeds that can be shipped while pushing is given by

$(B - A)(T_F - t_C)$. However, pushing has the negative impact of leading to a higher probability of returns.

In particular, pushing leads to returns of $[B(P_L + P_H) - AP_L](T_F - t_C)$. For the parameter values

established in table 1 ($T_A=5$, $T_B=1$, $P_L=0.1$, $P_H=0.5$), the positive effect of shipping more seeds is higher

(by almost 50%) than the negative impact of returns. Therefore, we make an *a priori* assumption that the

net impact of pushing is *advantageous* to the company.

The equation for the return fraction (7) has an intuitive interpretation. The minimum return

fraction, P_L, takes place when the critical time to switch from positioning to pushing is sufficiently high

($T_F \leq t_C \leq T$). When $r_S = P_L$, salespeople only position seeds and never push. The maximum return

fraction, $P_L + P_H$, occurs when t_C equals zero ($t_C = 0$). If the critical time to switch to pushing is zero,

salespeople will push seeds from the beginning of the quarter and returns will be given by the maximum

probability of shipping wrong seeds ($P_L + P_H$). Between these extreme conditions, the degree of excess returns, P_H, is given by:

$$\left(\frac{B(T_F - t_C)}{At_C + B(T_F - t_C)} \right) \tag{8}$$

Since the numerator in equation (8) provides the total amount of seeds pushed to dealers and the denominator gives the total amounts of seeds shipped, the ratio suggests that the degree of excess returns is proportional to the *fraction of seeds pushed* to dealers. Moreover, it is possible to characterize the critical time (t_C) from the definition of pressure in equation (3) and after we introduce t_C in the equation above, the return fraction can be expressed as (see appendix 2 for details on this derivation):

$$r_S = P_L + P_H \cdot Max\left[0,1 - \frac{A}{G/(1 - r_{S-1})} \cdot Min\left(\frac{p_T - 1}{p_T - AT \left/ \frac{G(1 + r_{S-1})}{(1 - r_{S-1})} \right.} T, T \right) \right] \tag{9}$$

This equation captures the dynamics of product returns in a multi-activity sales environment system by relating the fraction of seeds returned in a quarter, r_S, to the amount of seeds that can be positioned in a quarter (AT), the quarterly grower demand (G), the pressure threshold for pushing (p_T) and the return fraction in the previous quarter r_{S-1}. A phase plot relating the current return fraction, r_S, to the previous quarter return fraction, r_{S-1}, provides a graphical representation of the return map in equation (9). Repenning (2001) provides an interesting application of an analogous phase plot to understand the emergence and persistence of fire-fighting in multi-product development systems.
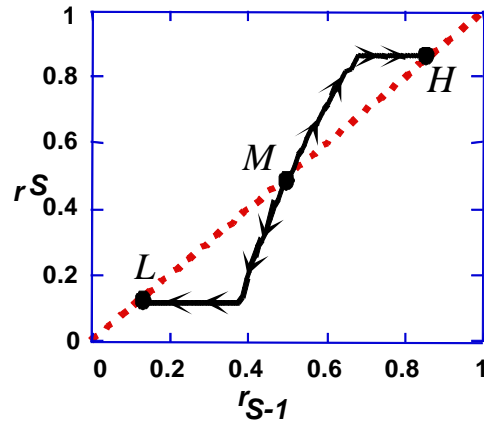
Figure 9. Phase plot for return fraction.

Note: Solid circles (fixed points) represent equilibria. The return fraction in the low (*L*) and high (*H*) equilibria are stable – once reached the system will remain there. The middle (*M*) equilibrium is unstable. A system starting close to (*M*) will follow the arrows toward one of the two stable equilibria.

To interpret the dynamics represented by the phase plot, shown in figure 9, start with a point in the x-axis, referring to the return fraction in the previous quarter, r_{S-1}, and through the phase function find the associated value on the y-axis, the current return fraction, r_S. To find the return fraction in the next quarter, r_{S+1}, start with the value obtained for r_S on the x-axis. Repeating the process allows us to obtain a summary of the evolution of the return fraction in the system. Note that any time the phase plot crosses the forty five degree line, the return fraction in the previous quarter will equal the current return fraction ($r_S = r_{S-1}$). Since the system is a one-dimensional map, these are the fixed points where the system is in equilibrium. Fixed points where the phase plot has a slope less than 1 are stable (e.g., the low (*L*) and high (*H*) equilibria.) Balancing feedbacks dominate the dynamics of the system such that departures from equilibrium are counteracted. Once these fixed points are reached, the system will remain there. In contrast, fixed points where the phase plot has a slope greater than 1 are unstable (e.g., the middle (*M*) equilibrium). Positive feedbacks dominate the dynamics around unstable equilibria; departures from these fixed points are reinforced, following the trajectory indicated by the arrows on the phase plot. Hence, if the system starts with a return fraction (r_{S-1}) *below* the unstable equilibrium, the positive loop will operate in a *virtuous* way moving the system toward the equilibrium with a low return fraction (*L*). If instead, the system starts with a return fraction (r_{S-1}) *above* the unstable equilibrium, the positive loop will operate in a

vicious way moving the system toward the equilibrium with a high return fraction (*H*). The unstable equilibrium, or *tipping point*, determines the position where the positive returns loop *changes* direction, or *tips*, from a *virtuous* operation mode to a *vicious* one, and vice-versa.

There are important implications of these insights. First, the existence of an unstable equilibrium that allows for a tipping point suggests that even when the system starts in the desired operation mode, there is no guarantee that it will remain there. This insight explains the difference in the dynamic behavior observed in the two simulation experiments above. In the base case, the system operates in a desired operation mode with a low return fraction. While the five percent increase in grower demand leads to a higher return fraction in the current year, it is insufficient to push the system beyond the tipping point, so the system returns to the original equilibrium. However, the ten percent increase in grower demand is large enough to push the system beyond the unstable equilibrium, taking the system to the equilibrium with high return fraction. Finally, the existence of the stable equilibrium with high returns ($r_S = P_L + P_H$) suggests that the problem of high returns can be a steady-state phenomenon to seed suppliers.

6.4. Characterizing possible system phase plots

The analysis above provides an explanation of how a sufficiently large shock can push the system beyond the tipping point, leading to an undesired mode of operation with a high return fraction. Here, we characterize the conditions under which the unstable equilibrium arises in the system. The conditions that contribute to the existence of a tipping point are obtained through analysis of equation (9). When the maximum constraint binds at zero, the equilibrium return fraction is simply $r_S = P_L$, indicating that a single equilibrium with low returns exists. To analyze which conditions allow the maximum constraint to bind at zero, we must first look at the minimum constrain. The minimum constraint will bind at the value of *T*, only if the number of seeds that can be positioned in the quarter (*AT*) is larger than the total seeds that the supplier must ship out $\left(G(1 + r_{S-1})/(1 - r_{S-1})\right)$, consisting of the sum total dealer orders $\left(G/(1 - r_{S-1})\right)$ and the amount of prior-quarter returns $\left(Gr_{S-1}/(1 - r_{S-1})\right)$. When the condition above holds, salespeople's choice of the pressure threshold (p_T) does not matter and the maximum constraint binds if

the number of seeds that can be positioned in the quarter (*AT*) is larger than total dealer orders $\left(G/\left(1-r_{S-1}\right)\right)$. Since the latter follows from the requirements for the minimum constraint to bind, we find that salespeople must have sufficient resources to position all desired shipments to dealers, regardless of the previous quarter returns (r_{S-1}). In the worst case scenario, the fraction of previous quarter returns would equal (P_L+P_H). Figure 10 shows the phase plot for the single equilibrium at $r_S = P_L$ when $AT > G\left(1+\left(P_L + P_H\right)\right)/\left(1-\left(P_L + P_H\right)\right)$. Intuitively, if sales resources are sufficient to enable all seeds to be positioned at all times no matter how high returns are, the system will always recover to a high performance equilibrium with the low return rate. Such a situation is highly unlikely, as the salesforce needed and the resulting costs would be prohibitive. A firm finding itself with so much sales capacity would almost surely downsize the sales organization to eliminate the excess capacity.

In contrast, when the positioning capacity (*AT*) is close to zero, which can happen if the time to position seeds (T_A) is extremely high, or the salesforce is so small that salespeople never position seeds, then the equilibrium return fraction is simply $r_S \cong P_L+P_H$. (The phase plot associated with this equilibrium is not shown.) Because salespeople have insufficient resources to position any seeds, they must push all of them to dealers. This high equilibrium return fraction $r_S = P_L+P_H$ is equivalent to the one obtained if the pressure threshold for pushing (p_T) is one (equivalent to a critical time, t_C, equal to zero). Intuitively, when there are so few resources relative to the workload requiring salespeople to push all the time, the system will always evolve to the high-return equilibrium even if demand temporarily falls. Firms would normally not reduce their salesforce capacity so much relative to the workload, forcing the sales system to always be in push mode. We therefore expect that this extreme condition is also likely to be rare (if for no other reason than that such a firm will have an uncompetitive rate of returns and either add sales resources or go out of business).

Three other general cases for the phase plots remain. Since in equilibrium $r_S = r_{S-1}$, we solve for the fixed points by substituting r_S for r_{S-1} in equation (9), yielding a quadratic equation in r_S. The equilibrium values of r_S are given by the roots of:

$$ar_S^2 + br_S + c = 0 \tag{10}$$

where:
$$a = p_T G + AT\left(1 - P_H\left(p_T - 1\right)\right)$$

$$b = p_T G\left(1 + \left(P_L + P_H\right)\right) - AT\left(1 - \left(P_L + P_H\right)\right)$$

$$c = p_T G\left(P_L + P_H\right) - AT\left(\left(P_L + P_H\right) + P_H\left(p_T - 1\right)\right)$$

The roots are: $r_{S1,2} = \left(-b \pm \sqrt{b^2 - 4ac}\right)/2a = \left(-b \pm \Delta\right)/2a$

Depending on the seed positioning capacity (AT), grower demand (G), the pressure threshold for pushing (p_T), and the probabilities (P_L, P_H), equation (10) may have zero roots (if $\Delta < 0$), one root (if $\Delta = 0$), or two real roots (if $\Delta > 0$), equivalently generating the same number of equilibria. Figure 10 shows these three general cases (and the previously mentioned case of a single low return equilibrium) as a function of the company's available resources for positioning seeds (AT). As the diagram suggests, as the company increases positioning capacity (AT) the shape of the phase plot changes from a system with a single low performance equilibrium (at $P_L + P_H$), to one with three equilibria – two stable (one low-return at P_L and one high-return) and one unstable – and then to one with a single high performance equilibrium (at P_L). (Note that the phase plot case with $\Delta = 0$ is not shown.)
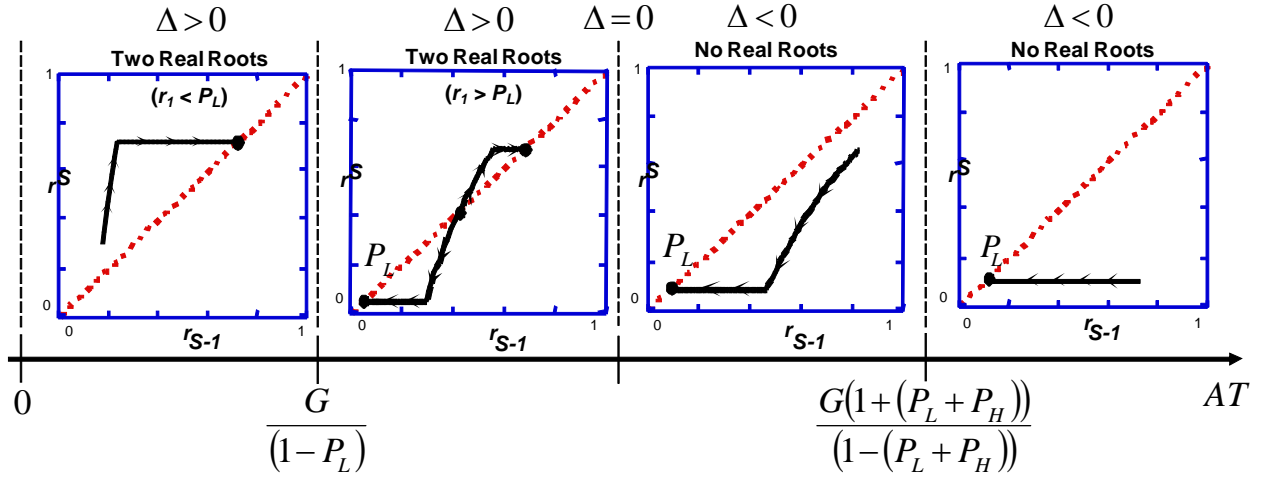
Figure 10. The system's phase plots.

The first case occurs when the supplier has *insufficient* resources to position the lowest possible amount of seeds demanded by dealers $(AT < G/(1 - P_L))$. Here, the quadratic equation has two real roots ($\Delta > 0$) but one of them lies below the minimum return fraction ($r_{S1} < P_L$). This situation can arise for different values of the pressure threshold for pushing (p_T). Here, the system has a single stable low-performance equilibrium with a high probability of returns and the positive loop of returns always works as a vicious cycle. Returns will be high but lower than $P_L + P_H$, because that can only be achieved if no seeds are positioned in the quarter. The second case arises when the supplier has *sufficient* resources to position the lowest possible amount of seeds demanded by dealers, $(AT > G/(1 - P_L))$, *insufficient* resources to position the maximum amount of seeds required by dealers, $AT < G(1 + (P_L + P_H))/(1 - (P_L + P_H))$, and the quadratic equation has *no real roots* ($\Delta < 0$). This situation arises when the pressure threshold (p_T) is high, allowing salespeople to use the available resources to position seeds. Here, the system has a single stable equilibrium at the low probability of returns ($r_S = P_L$), determined by the maximum function in equation 9 and not by the roots of the quadratic equation. In this situation, the positive loop of returns always works as a virtuous cycle. The final case arises when the supplier has *sufficient* resources to position the lowest possible amount of seeds demanded by dealers, $(AT > G/(1 - P_L))$, *insufficient* resources to position the maximum amount of

seeds required by dealers, $AT < G(1+(P_L+P_H))/(1-(P_L+P_H))$, and the quadratic equation has *two real roots* ($\Delta > 0$). Here, the system has two stable equilibria – one at the low probability of returns (P_L) and one at the high probability of returns – separated by one unstable equilibrium.

The unstable equilibrium is obtained by the smaller of the two roots and determines the location where the positive returns loop changes direction. Here, the positive loop can work either as a virtuous or a vicious cycle. Since companies may have sufficient resources to *position* some seeds $G/(1-P_L) < AT < G(1+(P_L+P_H))/(1-(P_L+P_H))$ and salespeople are unlike to adopt very high pressure thresholds (p_T), we should expect to observe this case frequently in the agribusiness industry. As figure 10 suggests, the amount of positioning resources (AT) influences the location of the unstable equilibrium. The fewer resources available, the closer the unstable equilibrium will be to the low-returns equilibrium ($r_S = P_L$), indicating that smaller shocks are capable of tipping the system into the undesirable operating mode. Therefore, it is important to recognize that resources not only affect the ability of the system to attain the desired operation mode (with low returns) but also determine the vulnerability of the system to shocks that can cause it to degenerate into the undesirable operation mode.

6.5. Incentives dependence on sales resources

Another important consequence of the availability of sales resources is the impact it has on the ability of incentives to dealers to curb the high return problem. That is, the effectiveness of incentives (e.g., penalizing dealers for inflated orders) depends on the availability of sales resources. Clearly, the lack of adequate incentives to dealers contributes to the volume of returns. Dealers face significant penalties for under-stocking corn-seeds, including sales and reputation losses, but no penalties for over-ordering seeds. An incentive scheme that penalizes dealers for high returns would likely reduce the amount of inflated orders and should be a part of a prescription to solve the problem. However, our analysis suggests that sufficiently low sales resources can make dealer incentives ineffective in solving the high return problem.

Consider the following incentive scheme that charges dealers a penalty for returns (βM). On one

extreme, when there is no penalty for returns ($\beta=0$) dealers over–order by a factor of $1/(1-r_{S-1})$. On

another extreme, a maximum penalty charge of M ($\beta=1$) can be defined as the amount that causes dealers

to order exactly the grower demand (over–order factor of 1). Under this incentive scheme, a penalty

fraction of β $(0 \leq \beta \leq 1)$ leads to an over–order factor of $\dfrac{1-\beta \cdot r_{S-1}}{1-r_{S-1}}$, directly reducing dealer orders (O_S)

to $\dfrac{G(1-\beta \cdot r_{S-1})}{(1-r_{S-1})}$ and next period returns to $\dfrac{Gr_{S-1}(1-\beta \cdot r_{S-1})}{(1-r_{S-1})}$. Indirectly, this incentive scheme reduces

the pressure experienced by salespeople, since low returns translate into lower shipment targets and also

smaller last period returns from which to recover. It is worth investigating fractional penalty charges

because such an incentive scheme would likely face significant barriers, particularly in industries that

traditionally do not adopt them. Managers at the seed supplier were unwilling to penalize dealers and

would not implement the most severe version of a penalty policy. They held a strong belief that penalty

for returns would lead to loss of sales and market share, especially because competitors did not have

similar policies in place.

Rewriting equation 9, which characterizes the fraction of returns, to incorporate the impact of an

incentive that penalizes dealers for returns, leads to:

$$r_S = P_L + P_H \cdot Max\left(0,1-\frac{A}{\dfrac{G(1-\beta \cdot r_{S-1})}{(1-r_{S-1})}} \cdot Min\left(\frac{p_T - 1}{p_T - \dfrac{A}{\dfrac{G(1-\beta \cdot r_{S-1})}{(1-r_{S-1})}} \cdot \dfrac{T}{(1+r_{S-1})}}T,T\right)\right) \quad (11)$$

Equation 11 captures both the direct and indirect effects associated with the incentive scheme.

Figure 11 shows the results of the dealer incentive for two different levels of penalties imposed: 10% and

20% of the maximum penalty (i.e., $\beta = 0.1$ and $\beta = 0.2$). Higher values of β can bring the system back to

the desired operation mode of low returns more quickly, but also face more resistance from management.

For the initial level of sales resource parameters (420 salespeople working 50 hours a week), the two penalty levels allow the seed supplier to recover from the 10% increase in demand. By reducing the amount of dealer overordering and pressure on salespeople, the policy prevents the system from being pushed beyond the unstable equilibrium by the 10% shock. Hence, the traditional explanation that dealer incentives are part of a solution to this problem holds as expected.
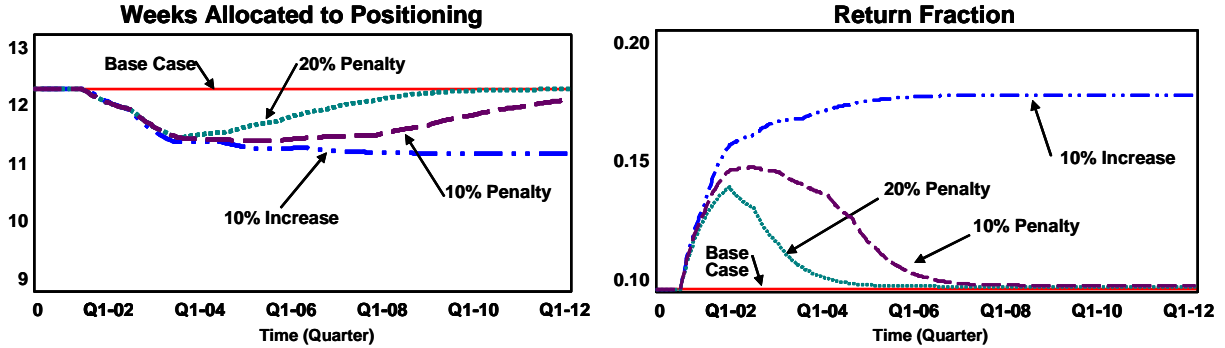

Figure 11. Dealer penalty: (a) weeks allocated to positioning and (b) return fraction.

Because the fraction of returns (r_S) depends not only on dealer orders but also on the amount of sales resources available to position seeds (AT), however, the effectiveness of penalty charges are likely depend on the availability of sales resources. To investigate this interdependency, we introduce a parameter to capture the fractional change in sales resources (γ). Incorporating the fractional change in sales resources in the fraction of returns equation leads to:

$$r_S = P_L + P_H \cdot Max\left(0,1 - \frac{\frac{(1+\gamma)A}{G(1-\beta \cdot r_{S-1})}}{(1-r_{S-1})} \cdot Min\left(\frac{p_T - 1}{p_T - \frac{\frac{(1+\gamma)A}{G(1-\beta \cdot r_{S-1})}}{(1-r_{S-1})} \cdot \frac{T}{(1+r_{S-1})}} T, T\right)\right) \quad (12)$$

When we reduce available sales resources by about 10%, i.e., $\gamma = -0.1$ (380 salespeople working 50 hours a week) neither the 10% nor the 20% dealer penalty is capable of solving the problem anymore (Figure 12). With fewer available sales resources (380 salespeople), the transient 10% increase in demand requires a larger fraction of salespeople's time to be allocated to pushing seeds, resulting in a higher

fraction of seeds returned. Due to the susceptibility of system performance to the availability of sales resources, isolated consideration of incentives is likely to be ineffective.
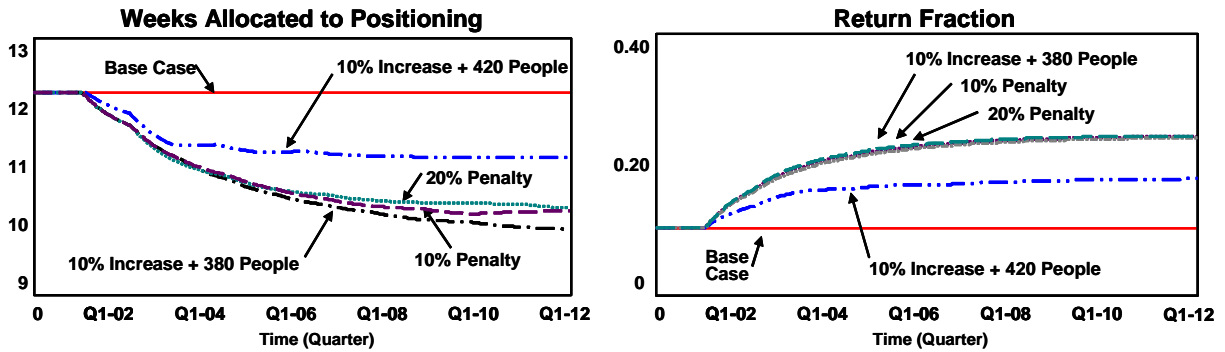

Figure 12. Dealer penalty with 10% fewer sales resources ($\gamma = -0.1$).

Now, consider the steady state performance of the system under both a penalty to dealers and a reduction in sales resources. Each point in figure 13 is an entire simulation showing (a) weeks allocated to positioning and (b) the final return fraction (on the vertical axis) for each combination of penalty level and salesforce size (on the horizontal ones). The graphs show that (a) stronger penalties for dealer overordering reduce the fraction of returns and increase the number of weeks allocated to positioning (for a given salesforce size); and (b) a smaller salesforce size increases the fraction of returns and reduces the number of weeks allocated to positioning (for a given penalty level). Thus, the effectiveness of dealer incentives depends on the adequacy of available sales resources. Insufficient sales resources increase the pressure faced by salespeople tilting their time allocation toward pushing more seeds, which ultimately lead to more seed returns.
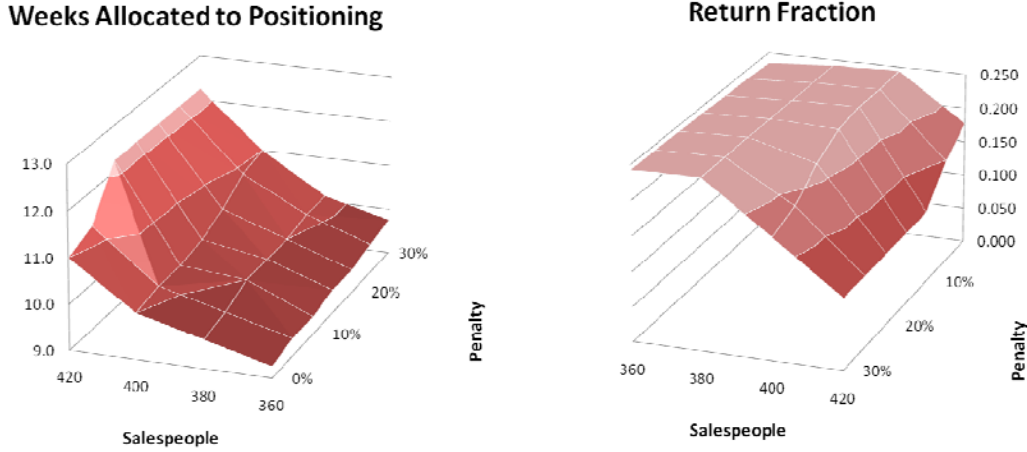
Figure 13. Steady-state system performance with different penalty levels and salesforce sizes.

Salespeople must make up for the entire revenue lost due to returns in the prior period (*S-1*). Considering the fraction (ϕ) of revenues lost in the previous period that needs to be recovered allows us to investigate how it may impact the effectiveness of the incentive scheme. Under this flexible revenue recovery plan a fraction of ϕ $(0 \leq \phi \leq 1)$ leads to a fraction of returns that must be shipped of $\phi G r_{S-1}$. The flexible revenue recovery plan reduces the pressure experienced by salespeople, since it reduces the target level that must be achieved by lowering the amount of last period returns from which to recover. Incorporating the fraction of revenues to recover (ϕ) leads to a revised equation for the fraction of returns:

$$r_S = P_L + P_H \cdot Max\left(0,1 - \frac{\frac{(1+\gamma)A}{G(1-\beta \cdot r_{S-1})}}{(1-r_{S-1})} \cdot Min\left(\frac{p_T - 1}{p_T - \frac{\frac{(1+\gamma)A}{G(1-\beta \cdot r_{S-1})}}{(1-r_{S-1})} \cdot \frac{T}{(1+\phi \cdot r_{S-1})}} T, T\right)\right) \quad (13)$$

When we reduce the fraction of revenues that salespeople must to recover to 75% (i.e., $\phi = 0.75$) we observe an improvement in the fraction of returns. Still, neither the 10% nor the 20% penalty is capable of solving the problem with a reduced workforce (Figure 14). A lower fraction of revenue lost to be recovered helps the overall performance of the system and it can be used as an additional lever to design a more effective incentive scheme.
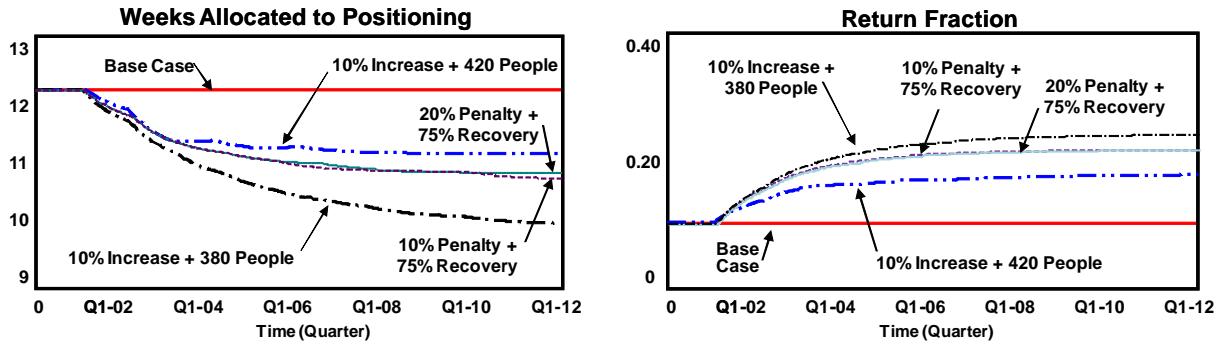
Figure 14. 75% fraction of revenue lost that must be recovered ($\phi = 0.75$).

In summary, this section highlights the interrelationships among incentive levels, sales force size and flexible recovery plans. Dealer penalties lower returns by reducing the amount of overordering. Increased sales resources lower returns by reducing the pressure faced by salespeople. Smaller fractions of revenues lost to be recovered also reduce the pressure experienced by salespeople, by decreasing the target level that must be achieved by salespeople. Interestingly, this sheds light at the effect of setting overly-aggressive sales goals. Aggressive goals lead to higher sales pressure, more time allocated to pushing and higher seed returns. Hence, stretch goals can detrimentally tilt the behavior of the system into a region where it cannot recover. The relationship established in equation 13 provides a guide to establishing goals that can motivate salespeople while not overextending their resources.

7. Discussion

Through a formal dynamic model of sales resource allocation in the agribusiness industry, we have shown that: (1) the interaction of sales effort allocation and dealer hoarding behavior can lead to high corn-seed return rates, and (2) this mechanism is self-reinforcing. Specifically, quarterly pressure to meet revenue targets late in the sales cycle cause sales representatives to abandon time-consuming seed positioning to push out dealers' inflated orders. More resources allocated to pushing seeds lead to short-term financial benefits but also result in higher seed returns the following period, generating more inflated orders by dealers and increasing the sales that agents must attain to reach their quota, leading to even more pressure

and more pushing the following period. The analysis highlights the importance of adequately managing sales resources to ensure desired system performance while maintaining system robustness.

The dynamics of the system show that salespeople making resource allocation decisions in multi-task sales environments face a "better-before-worse" trade-off (Repenning and Sterman 2001). The positive, but transient, consequence of pushing seeds is rapid, easy to assess and benefits mainly the individual sales representative. In contrast, the negative, but lasting, consequences occur with a delay and affect the whole system as seed returns accumulate the following season and degrade firm performance. Unfortunately, the biased allocation of resources toward tasks with higher short-term benefit is common in different settings (such as new product development, banking services, process improvement efforts, fisheries, etc.) especially under stressful conditions (Repenning 2001, Oliva and Sterman 2001, Repenning and Sterman 2002, Moxnes 1999). Initial errors resulting from this biased resource allocation are self-reinforcing, driving the system to a low performance, high-return equilibrium. A manager that does not understand the dynamics discussed above and interprets the ability to meet more aggressive goals with a smaller salesforce as a productivity improvement (Oliva and Sterman 2001) is likely to find her organization trapped in the low performance equilibrium. To prevent this, managers must focus on the system's ability to robustly handle the required tasks by carefully managing available sales resources.

While a traditional prescription to the problem described here would be to implement adequate incentives for dealers, our analysis shows that the effectiveness of incentives depends on the adequacy of available sales resources. Our analysis shows that stronger penalties for dealer overordering reduce the fraction of returns and increase the number of weeks allocated to positioning (for a given salesforce size); and that a smaller salesforce increases the fraction of returns and reduces the number of weeks allocated to positioning (for a given penalty level). Insufficient sales resources increase the pressure faced by salespeople tilting their time allocation toward pushing more seeds, which ultimately leads to more returns. Dealer incentives solve the dealer over-ordering problem. However, over-ordering is just one component of the seed returns problem. Returns take place both because of dealer over-ordering and salespeople's inadequate allocation of effort when faced with intense sales pressure. In turn, our research

shows that a number of parameters influence sales pressure: (1) availability of sales resources, (2) fraction of revenues lost from past year returns to be recovered and (3) sales targets. Increased sales resources, smaller fractions of revenues lost to be recovered, and moderate sales targets lower returns by reducing the pressure faced by salespeople. By understanding the causes of returns, our research informs us about the limitations of dealer incentives, shedding light on the important roles of adequate sales resources management and of setting moderate sales targets. Overly-aggressive sales targets lead to higher sales pressure, more time allocated to pushing and higher seed returns. Hence, stretch goals can detrimentally tilt the behavior of the system into a low performance region characterized by high returns. Because this behavior is self-reinforcing, even transient aggressive sales targets can permanently tilt the system into a poor performance equilibrium from which it may not easily recover.

The implications of this research are of general interest because the seed industry is similar to other high-technology, high-velocity industries characterized by short and unpredictable product lifecycles, rapid turnover of SKUs in the catalog, long product development and production delays, and volatile and unpredictable customer demand. In addition, due to fierce competition and the constant need to drive down costs, more and more companies in diverse industries face eroding sales capacity and increasing pressure to meet aggressive sales goals. As our study suggests limited resources and aggressive targets are the basic conditions required for the existence of tipping points in sales environments. Furthermore, as these conditions deteriorate, the system becomes more vulnerable to exogenous shocks, requiring smaller shocks to trap it into the undesirable operating mode.

7.1. Resilience of Returns

Even with proper incentives, adequate sales resources and moderate sales targets, there are strong behavioral and cognitive reasons why salespeople might allocate effort to pushing seeds. First, pushing seeds is more tangible than positioning seeds and people consistently over-weight salient and tangible features of the environment (Kahneman et al. 1982, Taylor and Fiske 1975). Second, pushing requires less effort and is less demanding than positioning. Third, whereas positioning does not lead directly to

sales pushing does and people are ambiguity averse (Einhorn and Hogarth 1985, Plous 1993). Fourth, the rewards accrued with pushing seeds occur closer in time to salespeople's actions and people exhibit time inconsistent preferences, favoring rewards that are closer in time (Loewenstein 1996, Angeletos et al. 2001). Together, these four considerations suggest that salespeople are unlikely to be rationally optimizing their time allocation based on a cost-benefit analysis, but that the salience of information and overweighting of immediate consequences strongly condition which information cues are used in their effort allocation decision, a strong behavioral effect.

7.2. Limitations and opportunities for future research

There are a number of limitations in the model. A simple anchoring and adjustment heuristic (Sterman 1989) drives production rate in the model. The anchor is given by the forecasted dealer orders, which assumes that dealers face the same underlying grower demand adjusted by the most recent return fraction. An inventory adjustment seeks to maintain current inventory at a target level. While production takes place during the fourth quarter only, we model it as taking place at the beginning of each quarter. In the model, seed inventory is replenished by production and seed returns and depleted by shipments. Since seeds have a maximum three year shelf-life, seed obsolescence should also draw from available inventory. However, we do not model seed obsolescence explicitly. We also do not incorporate inventory shrinkage and spoilage due to losses and poor storage conditions at dealers. Furthermore, while orders and returns happen over time, we model then as taking place at the beginning and end of the quarter, respectively. We assume that quarters are mathematically equivalent, but most dealer orders are placed in the fourth quarter (Q4), most returns take place in Q1, production occurs during Q4, and sales pressure at the end of Q4 is more intense than that at the end of Q1. The model does not account for the possible inflation of orders by growers competing for seed at the regional level (Gonçalves 2003, Sterman 2000).

A number of opportunities for future research also exist. First, book and drug returns in the publishing and healthcare industries, respectively, present prompt opportunities to apply the findings reported here. Book returns, averaging 35%, have been growing in large part due to the spread of

superstores and their increased ability to order large quantities of new books and then return them at no cost (Rogers and Tibben-Lembke 1999). At the same time, publishing industry sales have been decreasing, placing greater stress on salespeople to meet their revenue targets, which could lead to tipping points in publishing sales environments. Second, the focus of our research is on understanding the impact that salespeople pushing and pulling behavior has on inventory overage at dealers, which ultimately triggers seed returns. Alternatively, we could have explored the behaviors (e.g., diligent avoidance of sales pushing) that could have lead to inventory underage at dealers, which would lead to lost revenues due to lack of seed hybrids. Our research informs us that pushing behavior is a costly way of reducing the likelihood of underage. Alternatively, the research exploring the use of positioning behavior that leads to inventory underage could inform the cost associated with reducing the likelihood of returns. Finally, since the behaviors described in the paper are generated by a system dynamics simulation model, a promising area for future research is to test in a laboratory setting whether people react the way that our model predicts. One possibility for the experimental setting is to have subjects play the role of a salesperson that has to choose between two tasks: one that generates a good forecast but takes a long time to sell a certain quantity of goods and another that generates a poor forecast but takes little time to sell the same quantity of goods. In the base treatment, without a dealer incentive, the salesperson would have insufficient time to meet the sales target choosing only the good forecast task. In the incentive treatment, a target rebate leading to reduced dealer orders would allow sufficient time for the salesperson to meet the sales target using only the good forecast task. In the sales resource treatment, with a target rebate still in place, both tasks would take longer (emulating the reduction in sales resource) again limiting the amount of time that the subject has to meet the sales target using only the good forecast task. Additional treatments could control the impact of the sales target on subjects' performance and task choices. Subjects' behaviors in such treatments would allow a direct comparison between the experimental setting and the system dynamics model and would provide an additional test of the role of resources management in sales environments.

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Appendix 1

This appendix provides a detailed derivation for the return fraction in a quarter r_S, which we define as the ratio of the amount of seeds returned (RR) by the total seeds shipped (TS):

$$r_S = \frac{RR}{TS} = \frac{\int_0^T S \cdot P_W \, dt}{\int_0^T S \, dt} \tag{A1}$$

The instantaneous shipment rate (S) is determined by available sales resources and whether salespeople position seeds, shipping with the positioning rate (A), or push seeds at the pushing rate (B).

$$S = \alpha A + (1 - \alpha)B \quad \text{where } \alpha \text{ is given by: } \quad \alpha = \begin{cases} 1, & \text{if } p < p_T \\ 0, & \text{if } p \geq p_T \end{cases} \tag{A2}$$

and the pressure threshold (p_T) determines when salespeople shift from positioning to pushing seeds. Since a critical time (t_C) is associated with the pressure threshold (p_T), we can draw figure A1:

Figure A1. Critical time (t_C) triggering an immediate shift in effort allocation.

The change in variables from pressure threshold (p_T) to critical time (t_C) allows us to eliminate α and rewrite the interval of integration using t_C, resulting in the total amount of shipments (TS):

$$TS_S = \int_0^{t_C} A \, dt + \int_{t_C}^T B \, dt \tag{A3}$$

Recognizing that the *Overall Probability of Returns* (P_W) when salespeople position seeds is P_L and it is $P_L + P_H$ when salespeople push them and using the critical time in the interval of integration allows us to define the amount of seeds returned (RR) at the end of the quarter:

$$RR_S = \int_0^{t_C} AP_L \, dt + \int_{t_C}^{T} B(P_L + P_H) \, dt \tag{A4}$$

Substituting the equations for total seeds returned (*RR*) and total shipments (*TS*) into equation (A1), yields:

$$r_S = \frac{\int_0^{t_C} AP_L \, dt + \int_{t_C}^{T} B(P_L + P_H) \, dt}{\int_0^{t_C} A \, dt + \int_{t_C}^{T} B \, dt} \tag{A5}$$

If salespeople push early in the quarter (i.e., pressure threshold is low) or pushing is very effective (i.e., a significant amount of seeds are shipped to dealers), available resources might be sufficient to ship all dealer demand before the end of the quarter (*T*). Therefore, we allow for the possibility that shipments end at time T_F, where $T_F < T$. If $T_F = T$, the supplier may or may not be able to ship all dealer orders placed. Substituting the results above in the returns fraction, r_S, equation yields:

$$r_S = \frac{AP_L t_C + B(P_L + P_H)(T_F - t_C)}{At_C + B(T_F - t_C)} \tag{A6}$$

Simplifying and incorporating the maximum plausible value for the critical time t_C, yields:

$$r_S = P_L + P_H \, Max\left(0, \frac{B(T_F - t_C)}{At_C + B(T_F - t_C)}\right) \tag{A7}$$

If instead the change in effort allocation from positioning to pushing took place linearly over time starting at the critical time (t_C) associated with the pressure threshold (p_T), we would have figure A2:
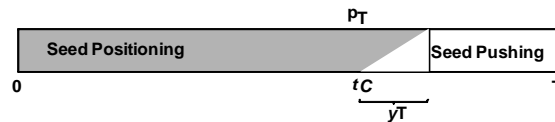

Figure A2. Critical time (t_C) triggering a linear shift in effort allocation.

Because we assume a linear transition from positioning to pushing taking place during *yT* (where *y* is a small fraction of the quarter *T*), salespeople would be positioning during half of the *yT* period and

pushing the other half. If we assume a linear transition from positioning to pushing takes place, we could

rewrite the equation A7 for the fraction of returns, such that:

$$r_S = P_L + P_H Max\left(0, \frac{B(T_F - (t_C + yT/2))}{A(t_C + yT/2) + B(T_F - (t_C + yT/2))}\right) \qquad (A7a)$$

Simplifying A7a with a variable change such that $t_L = (t_C + yT/2)$, we obtain:

$$r_S = P_L + P_H Max\left(0, \frac{B(T_F - t_L)}{At_L + B(T_F - t_L)}\right) \qquad (A7b)$$

Because equation A7b has the same form of A7, we find that whether the shift in effort allocation

takes place immediately or linearly over time does not impact the nature of the results.

Appendix 2

To reduce the high order nonlinear model dynamics to a one-dimensional map, we simplify equation (A7)

recognizing that the final time T_F is the time required to meet dealer demand $\left(\frac{G}{1 - r_{S-1}}\right)$ while positioning

and pushing seeds with the available sales resources $(At_C + B(T_F - t_C))$:

$$r_S = P_L + P_H Max\left(0, 1 - \frac{At_C}{G/(1 - r_{S-1})}\right) \qquad (A8)$$

It is possible to characterize the critical time (t_C) from the definition of pressure in equation (3)

and its components, equations (4) and (5). The threshold pressure is given by the ratio of the fractional

gap in revenues (RG_S) at the critical time and the fractional time remaining (TG_S):

$$p_T = \frac{\dfrac{(R_S^* + RL_{S-1}) - GR_S(t)}{(R_S^* + RL_{S-1})}}{\dfrac{T - t_C}{T}} \qquad (A9)$$

One simplifying assumption is required to obtain the lost revenues from previous quarter returns

(RL_{S-1}). We assume that the volume of seeds shipped in the previous quarter ($G/(1 - r_{S-2})$) is the same as

the volume sent out this quarter ($G/(1 - r_{S-1})$). This simplification allows the return fraction in a quarter to

depend only on the return fraction in the previous quarter (instead of the last two quarters) and it slightly

underestimates (overestimates) the critical pressure when returns are increasing (decreasing) from quarter

to quarter.

$$p_T = \left(1 - \frac{A \cdot t_C}{G(1 + r_{S-1})/(1 - r_{S-1})}\right) \Big/ \left(1 - \frac{t_C}{T}\right) \tag{A10}$$

Isolating the critical time (t_C) and conveniently arranging terms, we obtain:

$t_C = Min\left(\frac{p_T - 1}{p_T - F_P} T, T\right)$ where the fraction of seeds that can be positioned in the quarter (F_P) is:

$F_P = \frac{AT}{\dfrac{G(1 + r_{S-1})}{(1 - r_{S-1})}}$; and the nonlinearity prevents critical switching times that are larger than the duration of

the quarter (T). In the equation for F_P the denominator ($\dfrac{GT(1 + r_{S-1})}{(1 - r_{S-1})}$) captures the amount of seeds that

must be shipped in the quarter and the numerator (AT) determines the amount of seeds that *can* be

positioned in the quarter. If too many resources (salespeople's hours) are available, it is possible to have

$F_P > 1$, that is, the supplier can position more seeds than the amount required to ship. This would lead to

critical times higher than T, indicating that the salespeople would only position seeds. Within a quarter it

is convenient to capture only critical times that are lower than or equal to its duration.

While the pressure threshold (p_T) influences critical time (t_C), t_C changes with the fraction of units

positioned (F_P) as it depends on the return fraction from previous quarter (r_{S-1}). Since returns often

change from quarter to quarter, the critical time changes accordingly for a given pressure threshold

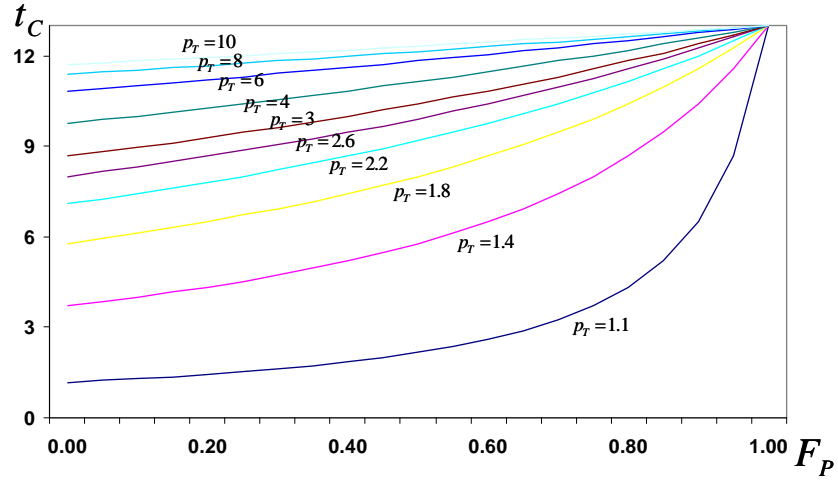according to the figure below (Figure A3).

Figure A3. Critical times (t_C) as function of fraction of seeds can be positioned (F_P).

We substitute the expression for critical time on the equation for the return fraction.

$$r_S = P_L + P_H \cdot Max\left(0,1 - \frac{A}{G/(1 - r_{S-1})} \cdot Min\left(\frac{p_T - 1}{p_T - F_P}T, T\right)\right) \tag{A11}$$

We obtain the final result for r_S when we introduce the result for the value of the fraction of units that can be positioned (F_P) on the equation above:

$$r_S = P_L + P_H \cdot Max\left(0,1 - \frac{A}{G/(1 - r_{S-1})} \cdot Min\left(\frac{p_T - 1}{p_T - AT\left/\frac{G(1 + r_{S-1})}{(1 - r_{S-1})}\right.}T, T\right)\right) \tag{A12}$$