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Enhancing New Product Development (NPD) Portfolio Performance by Shaping the Development Funnel

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Abstract

New product development (NPD) projects are typically managed through a series of screens, or gates, where ideas compete for resources. Ideas are carved into projects, and these projects are reviewed, and approved or terminated through the screening process so that only the best performing projects continue to subsequent stages of design, development and testing, and are released into the market place (Krishnan and Ulrich 2001; Terwiesch and Ulrich 2009). Most large innovative organizations deal with more than one NPD project at a time and typically engage in product pipeline management (PPM), where a set of active projects are evaluated together while they traverse through a sequence of such screens. Key decisions in a R&D pipeline are: screen thresholds, complexity of projects, resource allocation and capacity adjustment biases. We explore the impact of structural and behavioral aspects of these decisions through a simulation based analysis of a pharmaceutical dataset. Results establish concave relationships between value created at the end of pipeline and the resource allocation and complexity allocation biases, indicating optimizability and a limit for front loading practices.

Keywords: product development, ideas, projects, product pipeline management, development funnel, stage/gate, screening.

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Introduction

New product development (NPD) projects are typically managed through a series of screens, or gates, where ideas compete for resources. Ideas are carved into projects, and these projects are reviewed, and approved or terminated through the screening process so that only the best performing projects continue to subsequent stages of design, development and testing, and are released into the market place (Krishnan and Ulrich 2001; Terwiesch and Ulrich 2009). Most large innovative organizations deal with more than one NPD project at a time and typically engage in product pipeline management (PPM), where a set of active projects are evaluated together while they traverse through a sequence of such screens.

Some empirical studies have explored the patterns, best practices or benchmarks in the managerial decisions concerning PPM (Schmidt et al., 2008). There is considerable variation on the way such screening mechanisms are used. For instance, in the automotive industry, new platforms, such as Chrysler's mini-vans (e.g. the Plymouth Voyager in 1984) or Toyota's hybrid Prius (1997) are launched in an episodic manner. After such launches, the market place expects that new models of these products will be launched on a periodic, yearly basis, and it is rare in this industry to screen out an entire development project using the conventional stage gate process described by Cooper et al. (1998). Other industries may either offer more fungible product introduction opportunities (e.g. software development managers resort to versioning, see Cusumano and Selby, 1995), or may be driven by long cycles of development (e.g. pharmaceutical developments may have to screen out concepts several years after the initiation of a discovery process based on regulatory feedback (Hurtado, 2009)). We steer away from analyzing conventional phase-gate processes that do not screen out products, and instead focus on the funnels, and especially their fuzzy (uncertain) front ends (Khurana and Rosenthal, 1998; Zapata and Cantú, 2008; Jugend and Silva, 2012), where products have to go through fundamentally different kinds of assessments across a succession of screens that determinate the shape of the innovation funnel. In our definition, the shape of the innovation funnel is established by the number of projects in play at various phases of development awaiting a successive set of screens. Different industries consider widely different numbers of innovations at each phase for each innovation that is eventually launched (Terwiesch and Ulrich, op. cit., Figure 9-3).

How can managers improve their product pipeline performance? Answers to this key strategic question will depend on the formulation of the process, associated decision structures, and the definition of performance, while explicitly reflecting elements of resource availability, task complexity, risk, and the resolution of uncertainty. Wheelwright and Clark (1992) describe typical decision levers in this setting: resource allocation (allocating workers), selection of task complexity (defining number, size and relations between tasks), capacity utilization (work intensity), and the level of threshold (minimum quality or expected value) for passing through a screen and the frequency of screening. Resource allocation dictates the types and amounts of resources available for executing tasks before a project, or a cohort of projects, goes through a screen. Complexity selection defines the nature of these tasks, and the amount of resources it takes to complete these tasks. Even though the level of complexity at each stage is predetermined to a certain degree by the existence of a minimum number of tasks to be performed, and their sequence, it is fair to assume that there is considerable freedom to managers while deciding project activities. For example, Thomke and Fujimoto (2000) and Khurana and Rosenthal (1998) recommend the front loading of activities in a project, i.e. the increase in complexity and activities early in the development process, as a way of reducing uncertainty and the amount of rework or new work to be done later.

Capacity utilization affects the tradeoff between output quality (and thus the value created), and throughput. The total amount of resources available for allocation across stages is determined by a budgeting exercise (Chao et al., 2009) and is divided among the stages, so that each stage receives a fraction of the total. The selection of average complexity in any one stage, on the other hand, is not subject to such a global constraint. Product portfolio management deals with the problem of balancing these resources, complexity and allied uncertainties, even without accounting for screening effects. Inclusion of screening effects, and balancing resources and project task complexity across stages of the pipeline introduces time dependence into the portfolio management space.

Accordingly, PPM is a multifaceted problem that reflects the dynamics of the product development pipeline, and the understanding of how decisions variables interact to affect the shape of the pipeline (also called the funnel) and its innovation outcomes. It is a normal practice within the portfolio analysis literature to convert the joint outcome of allocated resources and selected complexity into the value created, which is typically measured in terms of net present value (NPV) of new-product projects (Cooper et al, op. cit.). The trade-offs between rate of value (or NPV) creation at each stage that is dictated by the above mentioned decisions and throughput of the pipeline needs explicit formulation and systematic study. Therefore, the goal of this paper is to provide policy insights for PPM decision-making by analyzing the underlying dynamics and determining which strategy allows a higher performance.

This PPM problem cannot be solved in closed form (Anderson and Morrice, 2006; Browning and Yassine, 2008). Furthermore, the pipeline interactions are difficult to study with traditional statistical methods or to anticipate with thought processes. A simulation study (Davis et al., 2007) is a particularly effective approach for tackling this problem because a model of portfolio value creation and throughput can be formulated to include multiple decision parameters and associated longitudinal interactions within a process involving multiple projects.

We developed a simulation model of the pipeline management problem, and then calibrated and tested it with data from a biotech company. The model is designed to determine guidelines for key simultaneous managerial decisions: choosing task complexity, allocating scarce resources and adjusting product development capacity. It employs screens with quality adjustment mechanisms, which select only those projects with higher expected value (NPV). The model allows the effort allocated to projects to be front-loaded in terms of average task complexity-- doing more work in an early stage to characterize and justify the projects. Because such frontloading delays the project's proceeding to the next stage of development, the shape of the pipeline, and the backlogs from one stage to the next, will consequently change depending on how teams will adjust to the changes in workload. The model calculates the overall long-term pipeline performance resulting from different combinations of decision parameters, in terms of the total expected NPV of completed projects. It also provides a mechanism to compute the elasticity of the outcomes with respect to intermediate thresholds and managerial choices.

The contributions from our work are three fold. First, we establish a simulation-based methodology to assess pipeline management and considerations of project throughput and quality. Second, we find that both the allocation of resources and the selection of complexity exhibit convexity that establishes limits to the advantage of front loading across a portfolio of products, i.e., there is an interior, optimal level for these variables that is not on the extreme sides of the performance curve. Third, the optimal level of resources and project complexity depends on interactions of these variables along with selected level of screens. We discuss the managerial implications, both structural and behavioral, of these findings.

We proceed as follows: §2 presents theory on the pipeline management phenomenon. § 3 operationalizes the theory and describes the PPM model. §4 identifies the design of the simulation study. §5 contains the statistical analysis of the results from the simulation study. Section 6 discusses managerial implications of these results and limitations. Section 7 concludes.

Theory

This section presents the theory used to develop the system dynamics model of the product development pipeline used in the study. All the definitions presented here are key to the understanding of the PPM model formulation.

The process of product pipeline management has been formulated as a dynamic resource allocation problem that is often beset with congestion effects due to resource constraints (Reinertsen 1997, Griffin 1997, Cusumano and Nobeoka 1998, Ulrich and Eppinger 2004). Decision rules for PPM have begun to be explored from various viewpoints: cycle time implications (Adler et al. 1995); stagewise resource allocation (Banerjee and Hopp, 2001). More recently, resource allocation insights have been formulated from a behavioral viewpoint, in terms of heuristics for resource allocation across multiple stages of a pharmaceutical R&D process (Gino and Pisano, 2005).

Allied studies within any one project have demonstrated the importance of overlapping (Terwiesch and Loch 1999; Bhuiyan et al., 2004; Marujo, 2009) and front loading development activities (Thomke and Fujimoto, 2000), meaning that more time/resources are invested on each project on early stages thus reducing uncertainty and subsequent rework. Thomke and Fujimoto's rationale is based on information exchange theory that rewards early exchange of information and problem solving. However, the front-loading logic for a portfolio of projects differs from its counterpart within a single project due to the aggregate considerations of resource allocation and complexity which are central to the PPM problem. The front loading of average complexity means that tasks for every project will be more complex and costly. This is a concept similar to the aforementioned one. The front loading of global resources, however, is related to the overall capacity to move projects to the second stage, and not to the complexity of a single project. In addition, at the portfolio level there is a need to consider the effects of screening thresholds and allied controls (e.g. resource utilization efficiency) that are also associated with these decisions.

Implications

A series of propositions or hypotheses to be tested in the study is presented on the following subsections, based on key structural aspects of PPM and tradeoffs inherent to the activity. However a focus must be put on the key implications from the hypothesis testing process.

First and foremost, it is found that both the allocation of resources and the selection of complexity exhibit convexity that establishes optimal levels and limits to the advantage of front loading across a portfolio of products. This finding is not obvious in the sense that in the available empirical literature (e.g. Thomke and Fujimoto, 2000, Khurana and Rosenthal, 1998), front loading is recommended but there is no tool to determine exactly how much or up to which level it should be implemented. The existence of optimal levels is also not obvious since the problem cannot be solved in closed form, i.e. it is an NP hard problem (Anderson and Morrice 2006; Browning and Yassine 2008).

Second, the optimal level of resources and project complexity depends on interactions of these variables along with selected level of screens. In this study it was found that there are many significant interactions in the process, which contributed very significantly to explain the variation on the dataset. Such interactions were not previously studied and are significant problem faced by managers. When the level of one variable is adjusted, the optimal level of other variables may change. The simultaneous choice of these variables is further complicated by such interactions.

We discuss next how these findings were anticipated (and justified) by both physical economical aspects of the PPM process.

The Utilization – Performance Trade Off

In a product development pipeline, the available capacity of the development teams is adjusted locally in order to either adapt to the work demand of each stage of the chain or keep the utilization level around its nominal value. Therefore, we define the capacity utilization bias as a managerial tendency to work between these two extremes. The teams will work more or less intensively depending on the capacity adjustment choice. If more weight is given to the objective of achieving the fastest rate to reduce backlogs instead of the nominal utilization level, the increase in the value of the projects as they pass through the gates should be proportionally smaller, because the capacity utilization will be above or below its nominal levels (Girotra et al. 2005; Clark and Wheelwright, 1993). This trade-off is represented on figure 1.

On the other hand, more projects can be released if the teams work more intensively. This suggests a competing hypothesis.

The capacity adjustment bias, a tendency that managers might have while making the capacity adjustment decision, affects value creation only in two cases: a) when there is a penalty for working more intensively, i.e. the capacity utilization versus value creation curve is not flat (in such case it becomes advantageous to produce more); and b) when the pipeline has an overflow of projects and there are potentially high utilization rate(s), above 100%. When there is starvation of projects, the target capacity will always be the same (the maximum possible), regardless of the direction of the bias. In other words, when the maximum capacity is below 100%, it doesn't matter if managers have a bias towards achieving nominal capacity (100%) or towards reducing the backlogs faster. The target capacities in both cases will be the same. Therefore it is proposed that as long as there is a potential for high utilization rates (>100%) , an increase in the bias, at any one stage, towards reducing backlogs through the adjustment of capacity will 1) decrease the total value of the projects due to lower value creation, and 2) increase value due to higher completion rates. If value creation is constant (i.e. no tradeoff for value creation), a bias towards reducing backlogs will increase total value creation due to the possibility of enhancing the pipeline without penalty.

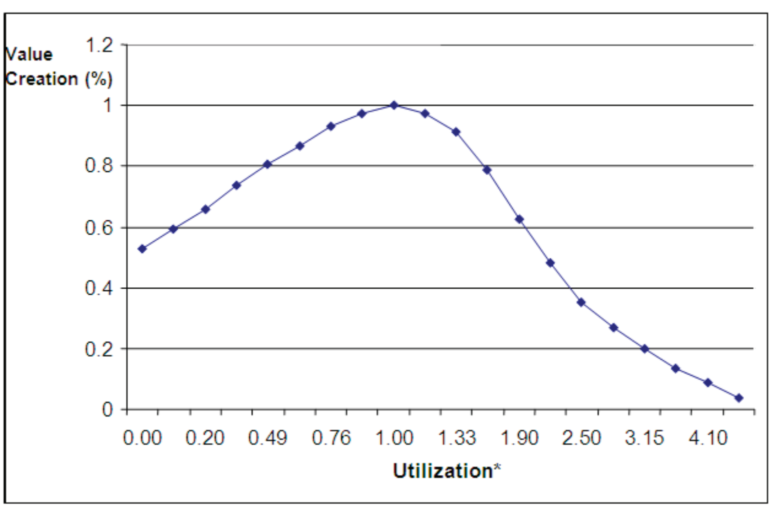

Figure 1: Relationship between Resource Utilization and NPV Creation Multiplier (Clark and Wheelwright, 1993)
*the nominal value of capacity utilization is set to be at unity.

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Resource Allocation

The market place rewards a steady delivery of projects, rather than a lumpy set of entries (Moorthy and PNG, 1992). Therefore, it is reasonable to assume that a choice of resource allocation fractions (basically how to allocate people across stages) that balances the pipeline, fine tuning the delivery of projects at its end will be preferable. Also, from a quantitative viewpoint, the NPV of projects in the late stages, being closer to the point of market launch, will exceed their early-stage counterpart. These considerations suggest that there will be both physical and economic limits to frontloading projects based on the need to construct a temporally balanced, high performance portfolio. The physical limits can be explained based on the assumption that the relationship between capacity utilization and value created in each gate has an inverted U shape; it is intuitive to expect that there exists an interior utilization level that maximizes firm profit. Utilization affects the dynamics across multiple stages in a product development pipeline and managers of the NPD pipeline can reallocate resources across stages, assigning people to other tasks in an attempt to optimize capacity utilization globally. Hence, we offer the following hypothesis to the front loading of resources: There is a limit to the gains made by front loading of resources for a portfolio of projects, while these projects traverse across a product development pipeline. We define resource allocation bias as tendency, while making the resource allocation decision, to allocate more resources to one stage than to another.

Complexity Selection

While it is easy to see why resources should be allocated to the front end from a problem-solving perspective for any one project (increasing task complexity of the initial phase), there is more to this picture (Cooper et al. 1998). All the activities in a project cannot be concentrated in the early stages. Indeed, behavioral evidence suggests that pipeline managers concentrate their attention on the last stage, due to a combination of focusing on recent events and allied hero mentality (Repenning et al. 2001).

We define average complexity as a measure of the number of, magnitude of and relationship between tasks. This is the metric that governs the nominal completion time, for a given amount of resources. Therefore, the average number of man-hours per project at each stage was used as a proxy for complexity in the model. Such proxy was also used by Yu, Figueiredo and Nascimento (2010). Indeed, allocation of average complexity for a project, is a dual problem, with respect to resource allocation (Browning and Yassine 2008). However, the decision on how much complexity gets allocated to a stage of any one project (a managerial tendency here called the complexity allocation bias) depends on the nature of the project portfolio. In the software sector, usually there are no such restrictions (McCormack et al 2001). But for physical technologies in tangible products, certain project tasks must follow others based on precedence relationship (Ford and Sterman, 1997), and all cannot be performed simultaneously upfront. Such sequencing of tasks reduces the average project complexity. Conversely, when other types of tasks can be pooled based on queuing considerations (Loch and Terwiesch, 1999) and executed within a single stage, the average complexity rises. There are also physical reasons for a limit to complexity allocation. Although a firm cannot always control the size of its projects, the number of manhours per project is a variable that affects how intensively the teams will have to work, therefore it affects capacity utilization. A longer time per project will result in an increase of capacity utilization and/or decrease in the number of projects released in the market. Therefore the relationship between project size and total value created should also be concave. Thus, we propose the following hypothesis to complexity allocation: There is a limit to the performance gains made by front loading of average complexity for a portfolio of projects, while these projects traverse across a product development pipeline.

Screening Threshold

The third set of decisions germane to the shape of the pipeline is the level of competition between projects (Terwiesch and Ulrich, 2009) and the associated screening threshold. Arguably, the higher the threshold, the lower will be the number of projects that pass through each of the screens and, accordingly, the lower would be the observed performance from the resulting set of product innovations. Accordingly, we suggest that the performance of the innovation pipeline is negatively associated with the screening threshold at each stage.

However, the direct effect of screening threshold on the performance does not complete the picture. Based on manager's allocation biases that are informed by the level of the reward and allied degree of difficulty (Frederick et al., 2002) there is endogeneity in the selection of screening levels and the participant's willingness to allocate resources and select the average task complexity. It is clear that depending on the selectiveness of the screening process, the optimal allocation of resources and complexity should change, because thresholds affect the shape of the funnel and number of projects at each stage. Thus, we make the following proposition: The optimal level of resource allocation and complexity allocation is mediated by the level of threshold at any one stage of the pipeline.

The NPD Pipeline Model

This section begins with a description of the NPD pipeline model, which defines all the key terms to the understanding of the pipeline. A detailed description of the model, with a list of equations can be found in Figueiredo and Loiola (2012) and Figueiredo and Joglekar (2007). The present study adds two variables to the model which were treated as a constant in Figueiredo and Souza: The average complexity of projects at each stage (measured by man-hours per project) and the fraction of resources (Man-hours per month) that are allocated to each stage (see equations 1 and 2 below and the original paper for more details). This section ends with an explanation of the calibration and validation processes.

$$\text{Utilization} = \frac{MIN\left(\left(\frac{Stage\ Backlog \cdot ManhoursPerProject}{NominalDevTime}\right), Available\ Capacity\right)}{Nominal\ Capacity} \qquad (1)$$

$$Stage\ to\ Review = MIN\left(\frac{Stage\ Backlog}{NOMINAL\ DEV\ TIME}, \frac{Available\ Capacity}{MANHOURS\ PER\ PROJECT}\right) \qquad (2)$$

Variable β (the resource allocation fraction) is a value between one and zero and is multiplied by the nominal capacity at each stage. The sum of β1, β2 and β3 is always equal to 100%. Therefore, resources can be allocated according do different policies, reflecting on the values of β.

Model Description

The dynamics of PPM involve a broad decision context. Any model that tries to mimic or reflect such decisions must incorporate these key decision processes. The structure of stocks and flows in PPM can be compared to the structure of a service supply chain model (Anderson et al. 2005). In both situations, the processing flow-time and capacity constraints have an impact on the throughput. The PPM problem is therefore a special case of service supply chains, where some projects are terminated across stages based on their NPV. Most firms use multiple gates in their pipelines (Ulrich and Eppinger 2004). For parsimony, our model incorporates only the first three gates, as shown in figure 2.

The basic structure and logic of the model are simple; every month, a certain number of projects is started and enters the pipeline. These projects are developed and screened in sequence, before being released into the marketplace. The NPVs of the population of projects are tracked, enabling managers to decide how many projects will be terminated and how much value will be lost due to termination. Value creation happens while projects are developed at each stage, and this value creation depends on how intensively the teams are working. Besides deciding on which projects will be terminated (i.e., defining a screening threshold (T) or minimum allowable NPV for a project to be approved), managers also decide on three variables: the capacity adjustment bias (α), the resource allocation across stages (β), and the average complexity of the projects (γ). Each of these vari-

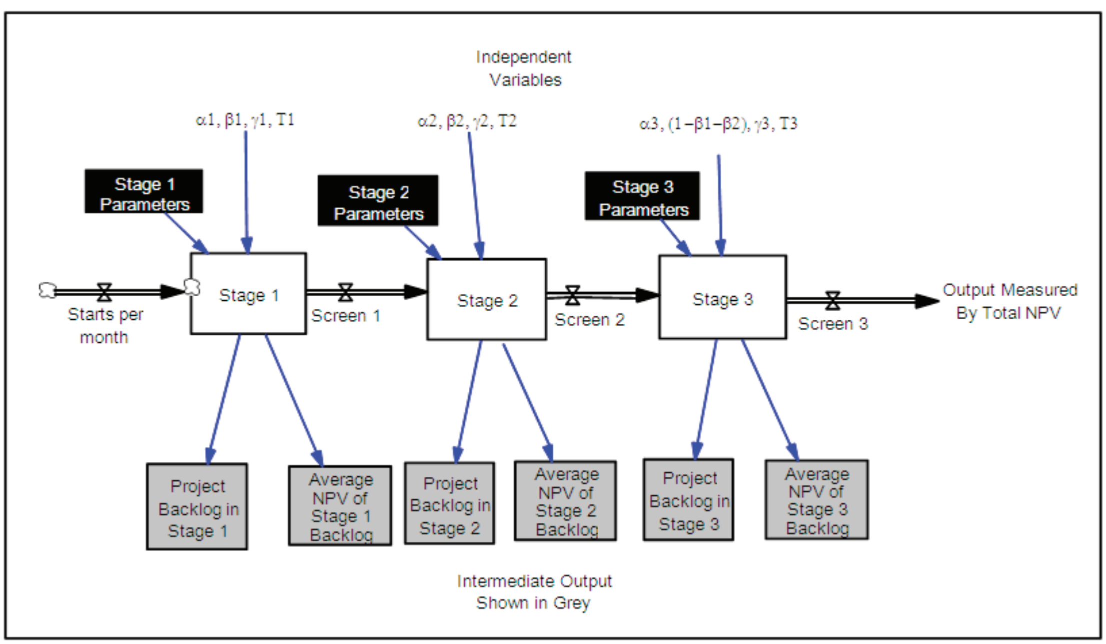

Figure 2: A Multi Stage Product Development Pipeline

ables affects capacity utilization (how intensively the teams are working) and therefore the value creation, as described on section 2.

The capacity adjustment bias reflects managers' tendencies between either working faster/slower in order to reduce the existing backlogs, or working at a constant rate (the best or nominal rate) to optimize value creation (see figure 3). The resource allocation bias reflects managers' tendencies to allocate more people to work on the initial, mid or final stages of the pipeline. Managers also have a bias towards allocation of complexity, i.e. they can choose to increase/decrease the complexity of the projects in any stage of the process. The performance variables in the model are the total value created (NPV) at the end of the pipeline, value creation rates at each stage and respective flows of projects. The adoption of NPV as the only performance criteria for project screening is a necessary simplification; in most companies, however, more than one factor is used to enable the decision to terminate a project, and different factors may be used depending on the stage of development of the project. For example, a pharmaceutical company might be more concerned with the safety of a substance at the early stages and with the manufacturability at later stages.
The PPM problem is structured as a dynamic process in the shape of a chain, therefore it is reasonable to assume that accumulation and/or starvation might happen in such a chain. Depending on the decisions made by managers, projects may accumulate in early stages, or the later stages may starve in case too many projects are terminated in early stages. The dynamic aspect of the pipeline adds complexity to the problem, and to the optimization effort.

Calibration

The model was calibrated to the Novartis Innovation Pipeline (Reyck et al. 2004). This case study has all the data necessary for the calibration, including NPV values at each stage, flows, complexity and resources. The Novartis pipeline has four stages, but the first stage (basic research) was excluded and only three stages were considered. The pipeline was calibrated for a steady state condition, in which value creation is maximum and there is a bias towards reducing the backlogs (α=1). In the calibration procedure, the following parameters were kept constant, consistent with the data set: starts, resource allocation fractions, average Project Complexity and Termination Rates. The following output was matched by performing an iterative adjustment of the Gumbel funtion look up tables, by changing the mean gain and variance, while keeping the nominal development times within reasonable range: Average backlog in each stage and Average NPV in each stage. The calibration achieved a goodness of fit of ±5% for all parameters, except the nominal development times.

Model Behavior and validation

Forrester and Senge (1980) suggest three types of tests of system dynamics models: (1) structural similarity to the actual system; (2) reasonable behavior over a wide range of input values; and (3) behavior similarity to actual systems. The

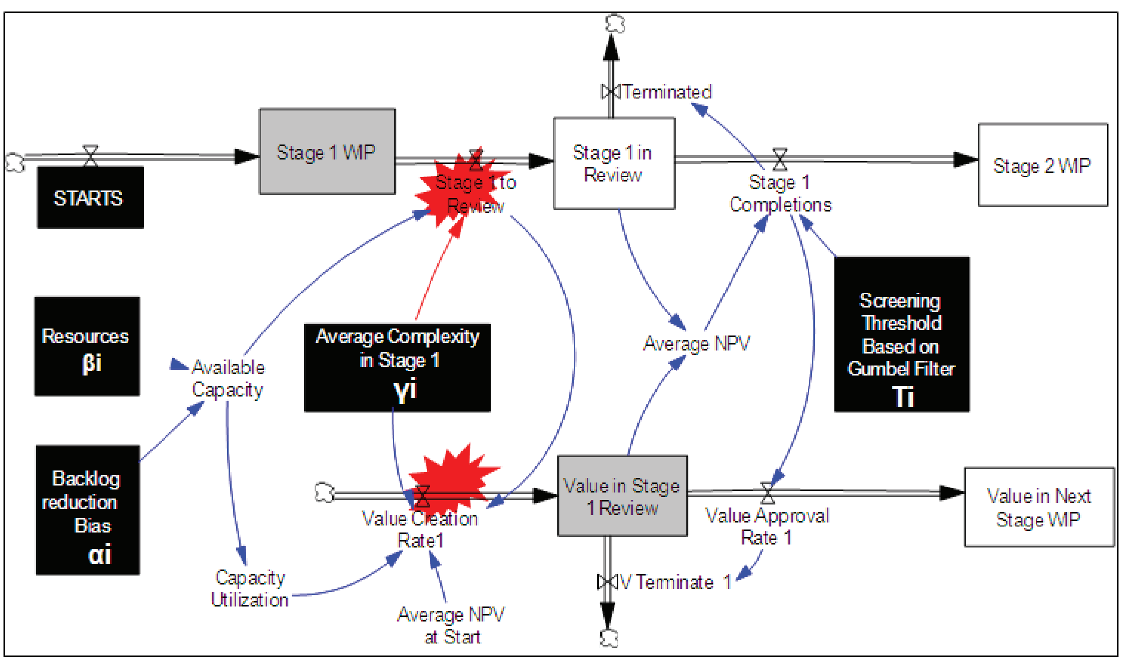

Figure 3: Stock and Flow Structure of a Typical Stage

model was tested under extreme conditions (see figures 5 to 7 and the next section) and it behaved well. Our experimental design used a wide range of input values. Model behavior remains reasonable through these tests. By basing the model on the PPM literature and on service profit chains, the model's structural similarity to PPM as practiced is improved. The data on actual product pipeline management allowed detailed model calibration and behavior comparison. The model behaved well in all studies.

In an attempt to increase external validity, a partial calibration for a dataset from Merck (Girotra et al. 2004) was repeated. In this calibration, only the average NPV values were not known, so nominal values were used instead. Similar results were obtained; the most important difference was that all 3 stages had significant parameters for Merck, instead of only the first stage for Novartis. The Merck calibration was modified by using the termination rates found in Schmidt et al (2008) for an industrial setting, and obtained similar results once again. It is clear that this study can be repeated for many other settings, by making certain assumptions depending on the availability of data.

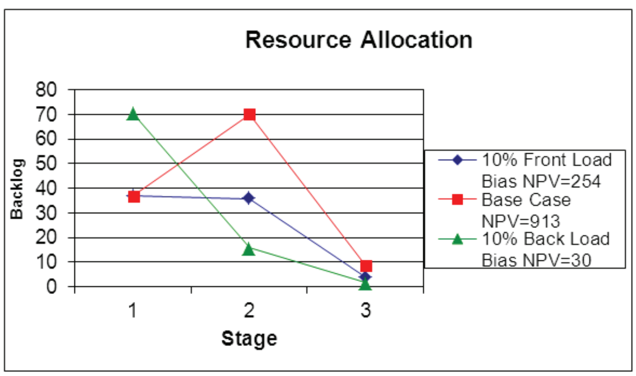

Figure 4: Effect of Varying the Resource Allocation Bias

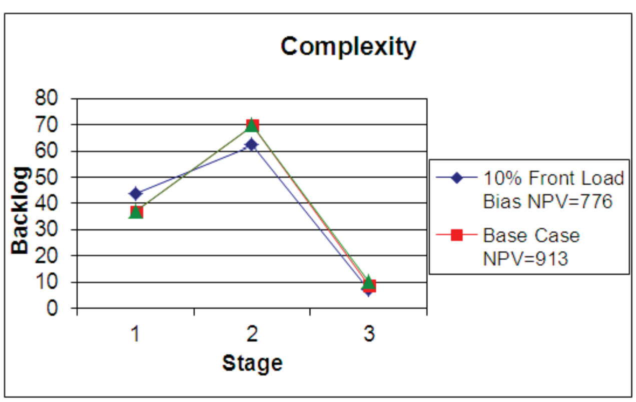

Figure 5: Effect of Varying the Complexity Selection Bias

Adding to these considerations, the model's behavior is consistent with the logics of product pipeline management as found in the literature. Also, by looking at figures 4, 5 and 6, it is easy to see how the shape of the pipeline can be determined not only by development time, but also by complexity and resource allocation. For example, by front loading resources, the backlog of stage 1 is reduced, and the backlog of stage 3 is increased, relative to the results of the back loading of resources. The opposite effect happens when complexity is front loaded. The effect of different configurations of the capacity adjustment bias is not significant because in this study the pipeline is not overloaded with projects, since the number of projects started is constant and balanced. When there was a larger inflow of projects, it was found that a bias towards reducing the backlogs in fact does reduce their sizes. Based on the above tests, the model is considered useful for analysis of the product pipeline.

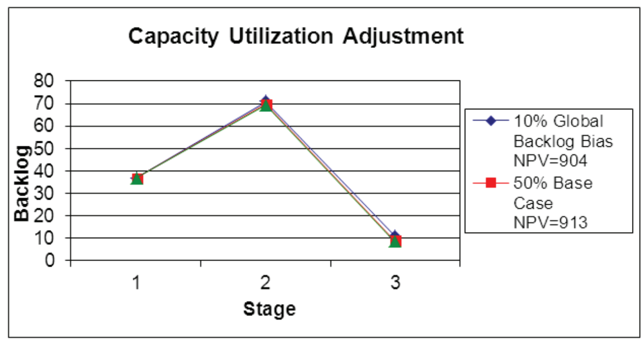

Figure 6: Effect of Varying the Capacity Utilization Bias

Experimental Design

Linear regressions were used to analyze the simulation dataset (as in Kleijnen 1995, Anderson et al 2005, Santos and Santos 2008). In this section, the specification of a regression equation and the design of the numerical experiment are presented.

Recall that the model has been set up with the NPV of the projects at the end of the third stage of the pipeline as the outcome variable that is shaped by resource allocation, complexity selection, resource utilization fraction, and screening thresholds across the first three stages. We use this set up to specify the following regression equation:

$$V = C0 + C1*\beta_1 + C2*\beta_1^2 + C3*\beta_2 + C4*\beta_2^2 + C5*\gamma_1 + C6*\gamma_1^2 + C7*\gamma_2 + C8*\gamma_2^2 + C9*\gamma_3 + C10*\gamma_3^2 + C11*\alpha_1 + C12*\alpha_2 + C13*\alpha_3 + C14*T1 + C15*T2 + C16*T3 + C17*\beta_1*T1 + C18*T_1*\gamma_1 + C19*\beta_1*\gamma 1 + \varepsilon$$

Here

i =1 2 3 represents stages of the pipeline

Cj = Regression coefficients, j=1, j=2…j=19

V: Total NPV at the end of the third stage of the pipeline at the end of planning horizon

ε: Noise Terms

Decisions

βi : increase in this parameter enhances resource allocation fraction for stages i, such that (βi >= 0 and β1+ β2+ β3=1)
γi : Complexity at stage i, such that γi >= 0
αi: Capacity adjustment bias at stage i (0<αi<1), Increasing this parameter reduces backlog instead of optimizing capacity utilization.
Ti: Screening threshold at stage i

This specification is used to test the propositions developed in §2 in the following manner.

All the linear terms of the relations between complexity and NPV created, and between resources and NPV created should be positive, since it can be shown that if a concave quadratic equation has its peak located in a point where X is positive (this is such a case, because resources and complexity are equal or more than zero), its linear coefficient must be positive. This proof is in the appendix A1.

For the hypothesis regarding resource allocation (hypothesis 1): we expect C1 and C3 to be positive and significant and C2 and C4 to be negative and significant. Such a result would mean that there is a limit to the gains made by front loading of resources, i.e., there is a concave relationship between allocation of resources and value created. This also means that it is possible to optimize such variable. For the hypothesis regarding allocation or choice of complexity (hypothesis 2): we expect C5, C7 and C9 to be positive and significant and C6, C8 and C10 to be negative and significant. In other words, there is a limit to the performance gains made by front loading of average complexity, because these coefficients are concave in relation to value created. Therefore there is also an optimal level for this variable. For the hypothesis related to managerial bias while adjusting capacity (hypothesis 3): there are competing hypotheses. We expect C11, C11 and C12 to be significant and positive/negative, meaning that an increase in the bias, at any one stage, towards reducing backlogs through the adjustment of capacity will either reduce or increase value creation. For the hypothesis regarding thresholds (hypothesis 4A): We expect C14, C15 and C16 to be negative and significant, meaning that higher thresholds for minimum NPV while screening projects will reduce the total value created. For the hypothesis related to interaction between variables affecting performance (hypothesis 4B): We expect C17, C18 and C19 to significant, which means that interactions are significant and the optimal level for one decision variable depends on the value of other(s).

Model Testing

One experimental condition was conducted in order to generate data. The condition was created to determine the model's behavior and generate policies in the presence of a tradeoff between capacity utilization and value creation.

The first study for the experimental condition, a.k.a. our base case, uses small perturbations to the parameters in the calibrated model described in section 3. This study aims to test hypotheses 1 through 4. One sensitivity analysis study is added to this base case: we run a scenario where there is no screening of projects, i.e. all projects are approved. This study represents an extreme conditions test (Forrester and Senge, 1980), because potentially high utilization rates are achieved, and ceiling effects might come into play in the pipeline.

The design of the base case uses the nominal value from the calibrated model that was described in section 3 as default or medium parameters (M_k,K=2). See tables 1 and 2. The nominal value of each decision parameter is then perturbed to a higher and a lower setting in order to create variations, to create three values (M_k, K=1,3). For example, while allocating resources, the total nominal capacity of stages 1, 2 and 3 remains fixed. However, it can be divided unevenly across stages to perturb the variable β That is, if β1 is raised by a factor of 5%, while keeping β2 constant, this means that stage 3 will proportionally lower amount of resources. Then a set of higher and lower values of β1 is selected (H_k and L_k, K=1,3) by adding or subtracting 5%. These parameters ensure that each segment of the utilization curve is sampled, without hitting extreme conditions. The selected complexity, i.e. needed number of man-hours per project in each stage is represented by decision variable Gamma (γi). The high and low conditions are calculated by adding or subtracting 5% to βi, 10% to γi and αi and ±0.5 standard deviations of the NPVs to the thresholds (Ti). These amounts of perturbations have been selected to span a large range of settings for the decision variables, while satisfying the constraints imposed by the table function used to calculate NPV creation rate based on utilization. For example, an increase of 5% in β1 results in an increase of 32% in the capacity of stage I.

This yields a partial factorial 7x7x7x7 design (see table 3), that requires a total of 2401 (i.e. N_{Base} = 2401) simulations.

Variable	Stage 1	Stage 2	Stage 3
NPV gain rate	3.3839	1.2599	3.1128
Average NPV (MUS$)	82.07	277.74	349.93
Backlog (projects)	37	60	5
Resource Allocation fraction (β)	0.1579	0.3816	0.4605
Complexity (γ) manhours/project*	112000	1082667	5226667
Starts	40 projects/year ±10%		
Termination Rates	75%	75%	20%

Table 1: Calibrated Parameters in the Base Case
*Assumed cost of manhour of $75

Stage	1	2	3
Flow: Base Case	10.1	2.59	2.146

Table 2: Flow Parameters the Base Case

α ,β γ,T	Stage 1	Stage 2	Stage 3
1	M1	M2	M3
2	H1	M2	M3
3	L1	M2	M3
4	M1	H2	M3
5	M1	L2	M3
6	M1	M2	H3
7	M1	M2	L3

Table 3: Experimental Design - Base case (n=2401)
*M=base case values, L=Low values, H=High values

Similar designs are repeated for the other studies. We note that the sensitivity study does not admit variation in thresholds. That is, NNo_Screens =343. The correlation matrix for the regression variables in the base case, is shown in Table 4.

Results

Experimental Condition 1: Capacity Utilization vs Value Creation Tradeoff

For the base case of condition 1, the regressions that examine hypotheses 1 through 4 are reported in Table 5. The sensitivity analysis results are reported in Table 6. Models 1 through 5 (corresponding to columns 1 to 5 respectively) examine perturbations to the base case. We only report the two most significant interactions.

We now review the results shown in models 3-5. Hypothesis 1 deals with diminishing returns on the variable βi. Coefficient C1 is positive and significant and C2 is negative and significant. . On the other hand, resource allocation for stage 2 is not significant. This suggests that for the set of base case parameters, the queuing physics of the pipeline makes the tuning and optimization of the first stage more important than that of the other stages. Thus, hypothesis 1 is supported for stage 1 in the base case.

Hypothesis 2 deals with diminishing returns on the variable γi. Coefficient C5 is positive and significant and C6 is negative and significant. Thus, this hypothesis is supported for stage 1 in the base case. Only the coefficients for the first stage are significant.

Hypothesis 3 deals with the utilization – performance trade off. This hypothesis is not supported in the base case, because coefficients C11, C12 and C13 are not significant. However, coefficients C12 and C13 were significant on the sensitivity analysis study. The deviation of results from the hypothesized pattern of behavior is further discussed in §5.2. Hypothesis 4A and 4B are related to the effect of the screening thresholds. Hypothesis 4A is supported because coefficients C14, C15 and C16 are significant and negative as expected. That is, higher thresholds result in more termination and value loss, as expected. Hypothesis 4B is partially confirmed: the optimal level of resource allocation is mediated by the level of threshold at the first stage of the pipeline. The level of complexity, on the other hand, is not mediated by the threshold since this interaction was not

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	T1	T2	T3	Alpha1	Alpha2	Alpha3	Gamma1	Gamma2	Gamma3	Beta1	Beta2	Beta1sq	Beta2sq	Gamma1sq	Gamma2sq	Gamma3sq
T1	1															
T2	.000	1														
T3	.000	.000	1													
Alpha1	.000	.000	.000	1												
Alpha2	.000	.000	.000	.000	1											
Alpha3	.000	.000	.000	.000	.000	1										
Gamma1	.000	.000	.000	.000	.000	.000	1									
Gamma2	.000	.000	.000	.000	.000	.000	.000	1								
Gamma3	.000	.000	.000	.000	.000	.000	.000	.000	1							
Beta1	.000	.000	.000	.000	.000	.000	.000	.000	.000	1						
Beta2	.000	.000	.000	.000	.000	.000	.000	.000	.000	.200**	1					
Beta1sq	.000	.000	.000	.000	.000	.000	.000	.000	.000	.994**	.199**	1				
Beta2sq	.000	.000	.000	.000	.000	.000	.000	.000	.000	.200**	.999**	.195**	1			
Gamma1sq	.000	.000	.000	.000	.000	.000	.999**	.000	.000	.000	.000	.000	.000	1		
Gamma2sq	.000	.000	.000	.000	.000	.000	.000	.999**	.000	.000	.000	.000	.000	-.001	1	
Gamma3sq	.000	.000	.000	.000	.000	.000	.000	.000	.999**	.000	.000	.000	.000	-.001	-.001	1

Table 4: Correlations Matrix – Base Case

Variable	Treatment	1	2	3	4	5	6 W/O Screening
Constant							
α1(Cap. Adjustment Bias)							
α2							2712.26* (60.39)
α3							1405.133* (60.39)
β1 (Front Loaded Resource)		n/a -1864.89	70085.237* -1860.85	70085.237* -6541.69	103409.699* -3392.77	27639.865* (2495.15)	50115.406*
β1 Squared		n/a -5882.17	-212751.85* -5869.45	-212751.85* -5836.24	-212751.85* -5621.27	-212751.85* (7870.12)	-150219.294*
β2 (Mid Loaded Resource)		n/a					
β2 Squared		n/a					
γ1 (Front Loaded Complexity)		n/a	n/a -0.028	0.079* -0.028	0.079*		
γ1 Squared		n/a	n/a 0	-3.5E-7* 0	-3.501E-7* 0	-3.501E-7*	
γ2 (Mid Loaded Complex.)		n/a	n/a				
γ2 Squared		n/a	n/a				
γ3(Back Loaded Complex.)		n/a	n/a				
γ3 Squared		n/a	n/a				
T1 -85.52		-566.988* -60.18	-566.988* -60.05	-566.988* -321.13	1108.786* -57.51	-566.988*	N/A

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T2	-695.05*	-695.050*	-695.05*	-695.050*	-695.050*	N/A
-67.52	-47.51	-47.41	-47.14	-45.4		
T3	-207.009*	-207.009*	-207.009*	-207.009*	-207.009*	N/A
(-16.34)	-11.5	-11.474	-11.41	-10.99		
T1β1	n/a	n/a	n/a -1998.27	-10612.89*	n/a	
β1γ1	n/a	n/a	n/a	n/a -0.026	0.379*	
Adj. R^2	**0.113**	**0.561**	**0.562**	**0.567**	**0.599**	**0.907**
F test and P value	51.745 0.000	307.183 0.000	193.845 0.000	186.184 0.000	211.623 0.000	257.604 0.000

Table 5: Results –Base Case, Condition 2
* P<0.01, ** P<0.05

significant. Other interactions are significant, signaling that the effect of one variable on performance usually depends on the value of other variables. For instance, β1γ1 was significant, which means that the optimal level of resources at the first stage depends on the chosen level of complexity.

Sensitivity Study:

The regression results are shown in column 6 for the additional study: no screening (100% of approval).

Model 6 admits extreme conditions. Recall from the base case that screening drowns out the capacity utilization bias towards minimizing the backlogs (i.e. H3 is not supported) at any stage. When there is no screening of projects, as shown in model 6, coefficients C12 and C13 become significant and positive, but C11 is not significant. This means that the capacity utilization bias is significant at stage 2 and 3. This "bottleneck shift" happens because when there is no termination, stages 2 and 3 become overloaded with projects with high utilization rates. We examine Table 7 to verify this. This table reports average flow rates for each stage, normalized with respect to the flow rates in the base case. Values above unity indicate a high utilization, and comparison across stages shows if the pipeline is balanced, on average. Thus, the backlog reduction bias makes a difference to the location of bottlenecks when no screens are place.

Stage	Study: Without Screening
1	3.98
2	15.42
3	18.63

Table 7: Average Flow Rates during Sensitivity Analysis (Normalized WRT Base Case Flow Rates), for condition 2

Discussion

We offer the following caveat before discussing the results. While the model structure is generic, the outcomes are crucially dependent on the nominal parameters, and on the key tradeoff between capacity utilization and value creation. We have run partial model tests on another data set from Merck (Girotra et al. 2004), and replicated the major findings. These results are available from the authors upon request. We have also used the model structure for an industrial setting (Schmidt et al. 2008), and in this instance the screening parameters yield results that are closer to our extreme condition test (no screening). We limit our discussion to the findings from the Novartis calibrated model.

The discussions for the experimental condition are grouped into a) the need to avoid blockages at the front end, i.e., how the front end can congest or starve later stages, and affect value creation as explained in section 3.1; b) pointers for pipeline design; and c) the potential for shifting bottlenecks, i.e. when managerial policies can change the flow rates of projects at different stages, affecting value creation and yielding different results in terms of which variables play a larger role in determining value creation

Avoiding Blockages in the Front End

The structure of the screening problem is like a queue with built in quality adjustment mechanisms. In such a queue, the front end can block the next stage. NPD literature recognizes the importance of the "fuzzy front end" (Khurana and

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Rosenthal 1997) and recommends a front loading strategy (Thomke and Fujimoto 2000) for a development process. These NPD studies have been empirical in their orientation and based on these observations, their authors argue for the need to focus on the front end owing either to the high amount of uncertainty or to the ability to generate early information. Consistent with these NPD findings (which refer to single projects), but based on pipeline management and throughput-quality tradeoff considerations, our analysis shows that management of "front end," i.e. stage 1, is important in governing the overall pipeline performance. Contrary to existing practices on multiproduct management (Repenning et al. 2001), the management of the fuzzy front end matters more to long term performance than trying to focus on the late stages of the pipeline.

Accounting for Convexity and Interactions during Pipeline Design

Confirmations of hypotheses 1 and 2 indicate that front loading of resources and average complexity selection in stage 1 are jointly concave in respect to pipeline performance. This means that these variables are optimizable and there are diminishing returns for them, as explained in section 2. Moreover, the results are dependent on the choice of thresholds and their interaction with the resources in stage 1 (as indicated by the confirmation of hypotheses 4). A managerial implication of these results is: when endowed with all the data, managers can fine tune the performance of their respective pipeline by following our procedure. Managers should be cognizant of the interactions between resources, complexity and thresholds, particularly at the front end of the pipeline. Such interactions are not accounted for in conventional portfolio analysis (Terwiesch and Ulrich 2009). The significance of interactions show that it is important to fine tune the pipeline in a consistent, holistic manner, because a change in one of the variables must be followed by a change in others, to account for the modification in the utilization rate and consequently in the value created. If one variable is adjusted, it can change the optimal level of others.

These findings also amplify the need for research on formal models for the pipeline outcome at any one stage, in terms of resources, complexity of screening threshold, particularly when that stage is the bottleneck. Similarly, the behavioral implications of the findings in terms of the propensity of an individual team at any one stage to pick higher or lower complexity, when given a fixed amount of resource, and given the historical probability of getting through a particular screen. We leave both these aspects as items for follow on work.

Screening and Starting, Value Creation and Screening Policies Shift Bottlenecks

Results from models 3-5 and 6, show that the PPM problem is not a conventional queuing problem, in the sense that managers are more interested in the value of the throughput, rather than just the waiting time. Moreover, there are two key state variables that co-flow (Sterman 2000): backlog and the total value of the portfolio at any one stage. In this structure, either the absence or the level of screens can shift the completion rates as shown in Table 7. Managerially, the implication for such shift implies that there is need to track the product resource allocation, complexity and NPV creation rates by stages. These data can be use to balance the pipeline and to change the screening levels endogenously if the pipeline is not balanced.

Another important effect of dynamics deals with the local biases captured in terms of the local capacity adjustment parameter (αi). In the case where there was no screening, potentially high capacity utilization are reached in stages 2 and 3, and the policy of working more intensively to reduce the backlogs is the best choice.

Conclusion

This study develops a set of hypotheses on the shaping and dynamics of the product development pipeline. A model is developed to assess pipeline management considerations of project throughput and quality, and data by means of simulation. The model is calibrated with data from a pharmaceutical setting. We find that the allocation of resources and the task complexity exhibit convexity that establishes optimizability and limits to the advantage of front loading across a portfolio of products. The optimal level of resources and project complexity depends on interactions of these variables along with selected level of screens and other variables.

Ours is a highly stylized model that comes with several limitations. For instance, we do not account for dependencies among projects, such as sharing of resources and sub-additive pay-offs. We have shown the model set up to portfolio managers in the bio-tech industry. They have pointed out that the model depends crucially upon the availability of reliable data on NPV estimation, and allied value creation rates, especially early in the pipeline. A second limitation is the manner in which some firms handle the idea generation process and define projects. Complexity in such setting may not be selected in an independent manner – certain projects must be lumped together while others must follow set sequences, and yet other set of tasks are viewed as platforms or may involve rework. Our model is aggregate and does not account for these effects. Moreover, shared resources affect the relationship between development costs and project development time (Girotra et al. 2005). Sub-additive pay-offs occur when a firm launches many products that are related (such as derivatives of a product family), but could generate the same revenues if it had developed only one product. Developing formal models of the economics of screening, in the presence of complexity and resource tradeoffs, either at a single stage or in a cascade of stages, and accounting for behavior bias (Gino and Pisano, 2005) offers opportunities for follow on work.

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Appendix

Linear term of the quadratic equations.
If performance is a quadratic equation of a variable x (complexity or resources) :
Value Created = Ax2+Bx+C (where A is negative and x is positive).
In the optimal point, where performance is maximum, we have:
0=2Ax+B so B=-2Ax. But we know that A<0 and x>0 at this point, therefore B>0.