# Do managers' heuristics affect R&D performance volatility?

# A simulation informed by the pharmaceutical industry

Francesca Gino
Harvard Business School
Morgan Hall 412
Soldiers Field Road
Boston, MA
fgino@hbs.edu

Gary Pisano
Harvard Business School
Morgan Hall 417
Soldiers Field Road
Boston, MA
gpisano@hbs.edu

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## Abstract

R&D performance volatility plays a critical role in various industries. Prior work in the innovation and product development literature has examined the factors influencing various dimensions of R&D performance. However, still little is known about the volatility of R&D output over time at the firm level. In this paper, we use a simulation model to explore such phenomenon, with a specific focus on the pharmaceutical industry. We argue that the fluctuations in R&D performance over time, while rooted in the uncertainty characterizing the development process, can be exacerbated by the heuristics decision makers use in managing the firm's R&D project portfolio. In particular, we focus on the impact on volatility of two types of heuristics: resource allocation and project termination strategies. Implications for both research and management practice are discussed.

## I. Introduction

R&D performance volatility is particularly pronounced in a number of industries such as entertainment, medical devices, semiconductors and pharmaceuticals. Volatility is a critical dimension of R&D output and is relevant to both practitioners and researchers. For instance, on the practical side, high levels of R&D output volatility contribute to cash flow volatility, which can have deleterious consequences for a firm's ability to fund attractive investment opportunities (Froot, Scharfstein, and Stein, 1994). Several studies have investigated organizational variables influencing such dimensions of R&D performance as lead times (Clark and Fujimoto, 1991; Ulrich and Eppinger, 2003; Krishnan, Eppinger and Whitney, 1997), productivity (Pisano, 1996; Henderson and Cockburn, 1996; Iansiti, 1997), and commercial success of new products (Fleming, 2001; Thomke, 2003). Far less attention has been paid to volatility of R&D output over time at the firm level.[2]

In this paper, we focus on volatility of performance in R&D. We assume that there is a certain level of "native" uncertainty in R&D processes that generates some degree of volatility. Given the technical or commercial uncertainty surrounding most types of R&D projects, it should not be surprising that R&D output fluctuates over time. However, we argue, the effect of such uncertainty can be magnified by the heuristics decision makers commonly use to manage their R&D project portfolio.

Assuming a fixed total R&D budget, the management problem is two fold: first, decide which projects to start, and then, decide which projects to continue and which to terminate at various stages of development, and how much to invest at each phase. In making these decisions, managers face a set of tradeoffs between risks, returns, and time horizons for payoffs. In theory,

[2] Only recently, firm-level volatility has been the focus of some research in the economics literature which has found that, over time, volatility of sales has decreased since 1984 at the aggregate level (Kim and Nelson, 1999; McConnell and Perez-Quiros, 2000) but has increased at the firm level (Comin and Mulani, 2004).

such tradeoffs are optimization problems that can be tackled with a technique such as dynamic programming. In reality, the complexity, ambiguity, and uncertainty of most companies' R&D portfolios make this an essentially impossible optimization problem to solve (Lockett and Gear, 1973). The decision-theoretic models proposed in the literature are themselves highly complex and, as a result, they have not become a tool that is commonly used in management practice (Loch and Kavadias, 2002). Given the complexity of the problem of both portfolio selection and management, and individuals' bounded rationality (Simon, 1956), it is not surprising that companies utilize heuristics for managing their R&D portfolios rather than trying to optimize. For instance, in an interview at a pharmaceutical company, the Chief Scientific Officer noted:

> "The R&D process is extremely complex, dynamic and sensitive to a wide range of internal and external factors... Business people will depend more on models because they are further from the details of the R&D process and can't easily distinguish between research programs and the specific inherent risk linked to them... For me, the importance of the model is in facilitating the conversation, getting the questions out, and helping interdisciplinary conversation."[3]

The idea that heuristics rather than optimization drive R&D decision-making was first introduced by March and Simon (1958). While behavioral approaches to R&D have become well accepted, research on the impact of specific heuristics on R&D performance is limited.

There are two main types of heuristics that firms commonly use in R&D portfolio management. The first refers to the heuristics used for prioritizing R&D investments across stages of the development process. The second refers to the heuristics used for determining which projects move forward and which ones to terminate. In this paper, we consider the case of pharmaceuticals and we focus on these two types of heuristics. To explore their impact on R&D performance volatility, we develop a simulation model of a multi-stage R&D process where

[3] Fleming, Lee, Gary P. Pisano, and Eli Strick. "Vertex Pharmaceuticals: R&D Portfolio Management." Harvard Business School Case 604-101.

firms can make decisions about investments in projects at each stage under a budget constraint, and decisions about project termination.

## II. R&D Performance Volatility: The Case of Pharmaceuticals

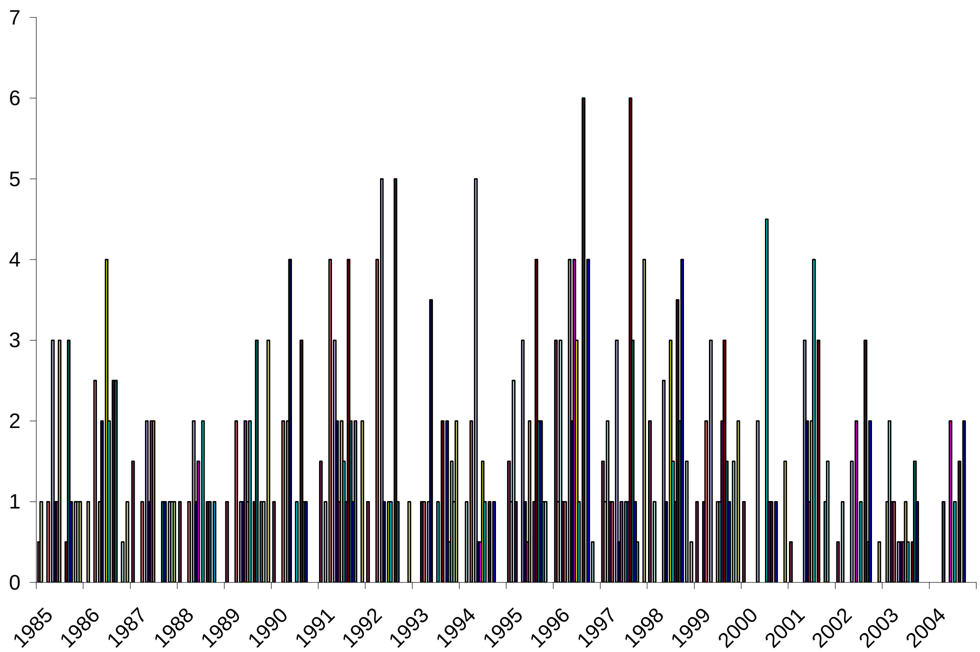
Volatility refers to the fluctuations in R&D performance over time. Figure 1 shows the yearly launches of new molecular entities (NMEs) for the 20 top pharmaceutical companies over a 20-year period.[4] R&D performance volatility is quite clear from Figure 1 despite the fact that R&D spending during this period was increasing monotonically.

R&D is inherently uncertain. To deal with this uncertainty at the level of the individual project, firms divide the process into discrete stages, such as research, concept development, detailed design, prototyping, manufacturing scale-up, etc. The number of stages in an R&D process varies by context but the logic behind staging is essentially the same: staging provides the firms discrete points in the process to exercise an option to terminate further development. In the case of pharmaceuticals, a major part of R&D consists of human clinical testing to assess safety and efficacy. The process is divided into 3 broad phases. Phase I focuses on safety, phase II on efficacy and appropriate dosing, and phase III encompasses tests of both safety and efficacy in a much larger sample of patients. One of the salient features of pharmaceutical R&D is that candidate drugs often fail during the process. Such failure is the result of a firm management's decision to terminate the project based on technical or non-technical reasons. On average, approximately 60% of drugs fail during phase I, 50% fail during phase II, and 15% fail during

[4] The list of such companies includes: Abbott Laboratories, Allergan Inc., Astrazeneca Plc., Bayer, Bristol-Myers Squibb Co., Elan Corp. Plc., Glaxo-Smith-Kline Plc., Johnson & Johnson, Lilly (Eli) & Co., Merck & Co., Novartis, Novo-Nordisk, Pfizer Inc., Roche Holdings Ltd., Sanofi-Aventis, Schering, Schering-Plough, Serono, Sterling Drug Inc., and Wyeth. To get a cleaner picture of R&D volatility over time, we looked only at those major companies that did not engage in significant mergers & acquisitions. Note that if a drug was developed by a company but launched by another, we attributed ½ product to each. *Source*: PharmaProjects database.

phase III (DiMasi, Hansen and Grabowski, 2003). Thus, on average, the probability of a drug entering clinical trials making it all the way to the market is approximately 17%.

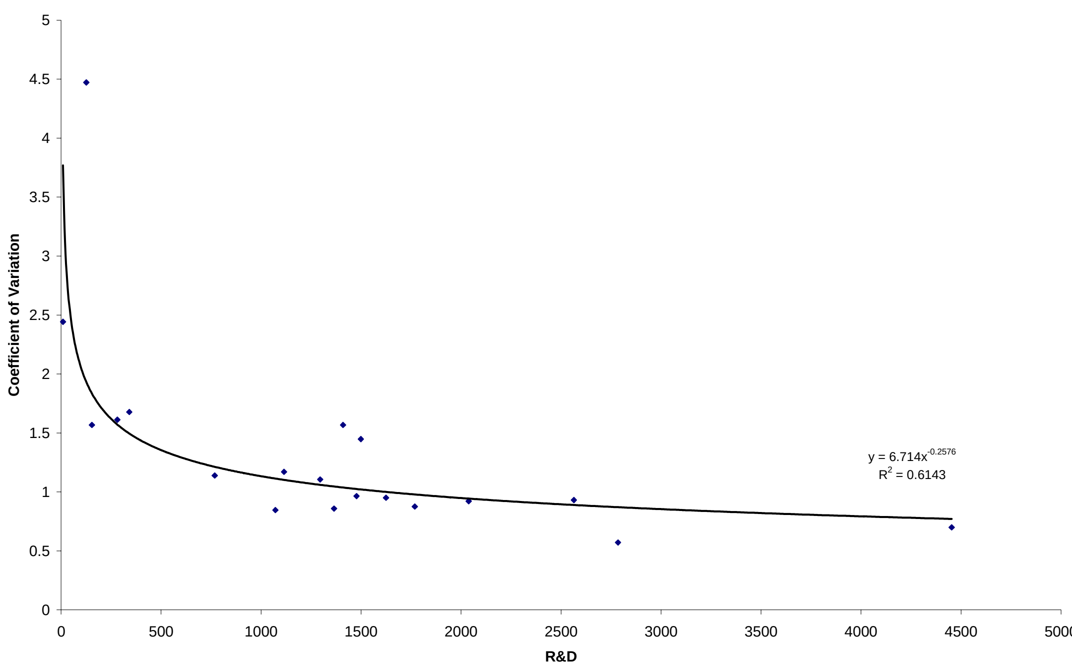
**Figure 1. Yearly launches of NMEs by company.**




Firms often use also a second practice to deal with uncertainty in the R&D process, namely portfolio diversification. While individual projects may be highly uncertain, the firm should be able to reduce its overall exposure by investing in a portfolio of R&D projects. The size of a firm's R&D portfolio is generally dictated by the firm's overall size. Empirical studies suggest that total R&D budgets are typically set as a fixed percentage of revenues, which may vary by firm and across industries. At any point in time, then, a firm can be viewed as holding a portfolio of R&D projects at various stages of development (for example, some early and some closer to commercialization). Given the large development costs for a single project in industries in which volatility is an issue, the strategy is to have a steady stream of projects at various stages of development, so as to secure the companies' viability in a certain period of time.

Figure 2 reports the relationship between scale (measured as R&D spending, in millions of dollars) and volatility (measured as the coefficient of variation in yearly launches of NMEs) for the 20 top pharmaceutical companies from 1985 to 2004.[5] As the picture shows, scale reduces volatility. In particular, as the trend-line reported in Figure 2 indicates, the relationship between scale and volatility is non-linear: while volatility can be reduced with an increase in the R&D spending, the effect is subject to diminishing returns. For small firms, volatility might be explained by the lack of resources needed to support the requisite size portfolio. But, the largest companies would appear to have these resources. For instance, in 2000, Merck publicly reported 51 internal R&D programs in various stages of development; Eli Lilly had 46; Bristol-Myers had 27 (Paraxel, 2000: 34).[6]

**Figure 2. Volatility of R&D output by R&D spending.**




[5] The coefficient of variation is computed as the ratio between the standard deviation of R&D output over a certain number of years and its mean. It thus captures the movement of yearly launches of NMEs relative to the mean.
[6] These numbers only include "internal" R&D programs, and exclude drug candidates licensed in from external sources. If one includes externally licensed-in compounds, the portfolios are even larger. Moreover, given the proprietary nature of drug company R&D portfolios, it is also quite likely that these publicly reported figures actually understate the total.

In essence, these firms appear to be doing what they should be doing: pursuing highly diversified R&D portfolios. Yet, despite this level of diversification, they still experience volatility, as Figure 2 shows. In essence, even after controlling for R&D spending, we observe differences across firms.

Given a certain R&D budget, can a firm reduce the volatility of its R&D output by changing the heuristics it uses to manage its R&D project portfolio? This paper explores this question. We suggest that there is room for firms to affect R&D performance in terms of both output and volatility by changing the heuristics they use in allocating resources to different phases of the development process and in deciding whether and when to terminate projects. While uncertainty (in lead times, project success, and cost of each development phase) sets the stage for volatility, heuristics in managing the R&D portfolio might exacerbate the effect of such uncertainty.

We investigate the impact of different heuristics in a 3-stage R&D process. The basic parameters of our R&D process are the number of phases, the cost, lead time and attrition rate for each phase and a fixed total R&D budget. After reproducing in our model the uncertainty in the R&D process, we conduct controlled experiments using computer simulations. Simulations, indeed, allow estimation of otherwise intractable models by portraying the dynamic behavior of systems over time (Pritsker, 1986). In the simulations, we change heuristics and study their impact on two dimensions of R&D performance, namely output and volatility. In the dynamics of the model, projects compete for resources and the firm, at each point in time, has to decide which projects get funded first and which projects to terminate. The conflict among resources is captured by holding the budget constant over time.

## III. A model for R&D portfolio management

Portfolio management is a dynamic decision process through which a list of active R&D projects is constantly updated and revised. In this process, new projects are evaluated, selected and prioritized; existing projects may be accelerated, terminated or de-prioritized; and resources are allocated and reallocated to the active projects (Cooper, Edgett and Kleinschmidt, 2001; Roussel, Saad, and Erickson, 1991). The portfolio decision process is characterized by uncertain and changing information, dynamic opportunities, multiple goals and strategic considerations, interdependence among projects, and involvement of several decision-makers (Cooper *et al.*, 2001).

In the innovation and product development literature, the problem of *managing* R&D portfolios has received much less attention than portfolio selection. A common assumption in the studies investigating the problem of portfolio management is that a given set of projects is initially specified (e.g., Banerjee and Hopp, 2001; Subramanian, Pekny, and Reklaitis, 2000). Different from previous studies, our model allows the set of initiated projects to vary over time.

### *Problem formulation*

In our model, a limited budget is initially specified ( $B$ ) and it remains constant over time. At each point in time, the firm allocates the budget to a portfolio of $M = \{1,...,m\}$ projects. The set of candidate projects that are available at each point in time is infinite; thus, whenever the firm wants to initiate a new project, a new project is generated. Each project $i$ must progress through $n$ stages sequentially. In our specification of the model, $n = 3$.

For each phase $j$ and project $i$ there is an expected lead time $lt_{i,j}$ expressed in terms of months required to complete the phase. Hence, the total lead time of project $i$ is given by

$lt_i = \sum_{j=1}^{n} lt_{i,j}$ . The time required to complete a phase is a random variable following a Weibull distribution.[7] Thus, there is uncertainty around lead times. Phase $j$ of project $i$ has a cost $c_{i,j}$ expressed in terms of dollars spent to complete the phase. Hence, the total cost of project $i$ is given by $c_i = \sum_{j=1}^{n} c_{i,j}$ . At each point in time, the firm sustains a cost equal to the average monthly cost for that phase. Since the phase lasts for a number of periods equal to the lead time, the overall cost the firm sustains to work on a project in a certain phase is the product between the average monthly cost and the lead time. Thus, in each phase, there is uncertainty around costs.

There is also an expected attrition rate for each phase $j$ of project $i$, $(1 - p_{i,j})$, which represents the percentage of projects that are expected not to progress from one phase to the next. Whether a project succeeds or fails becomes known only when the project completes a certain phase. More specifically, when a project completes a stage, it can be terminated or moved forward to the next stage, depending on a firm's decision. However, it can only move into the next stage if there are resources available to start and complete the phase. If resources are not available, the project waits in a queue. In particular, there are two buffers: one between phase I and phase II and the other between phase II and phase III. Once resources become available to the project, it can then enter the next phase.

A project is successfully completed when it makes it through all three phases. This implies that the probability of project success is given by $p_i = \prod_{j=1}^{n} p_{i,j}$ . Upon completion, each

[7] The Weibull distribution is often used to model "time until failure" (for instance in engineering work) because of the many shapes it attains for various values of its parameters. In our simulation, we chose the parameters so that the probability of obtaining a lead time longer than the average one observes in the pharmaceutical industry is higher than the probability of obtaining a shorter lead time, for each project and in each phase.

project $i$ yields an expected revenue of $\alpha_i$. To simplify the problem, we assume that each project has a constant return (i.e., projects are characterized by the same distribution of returns).[8]

The objective is to find a strategy that lets the firm manage its portfolio so as to maximize the R&D output and minimize volatility. Because we assume expected revenue does not vary across successful projects, this is equivalent to saying that the firm's objective is to maximize the expected net present value. For instance, if the focus is on resource allocation, the firm's objective is to find a strategy that allocates the available budget to projects so as to maximize the expected net present value.

A dynamic programming formulation for the general portfolio management model specified above could be developed. However, since the resulting problem would be too difficult to solve or analytically intractable (Lockett and Gear, 1973), we use computer simulations to explore the impact of different R&D portfolio management heuristics on R&D output and volatility.

*Simulation model*

In the basic simulation model, two parameters, T and M, govern the behavior of a modeled firm.[9] The total time T was set to 1920 months (i.e., 160 years) in each simulation and 100 iterations were run in each simulation set.[10] Results were then averaged over the 100 runs. At the beginning of each simulation, M projects are randomly generated based on the fixed

[8] We made this assumption since we are interested in the impact of heuristics on performance, measured as number of projects that successfully complete the R&D process and not as monetary return on investment.
[9] The type of simulation we implemented is a "non-terminating steady state simulation": there is no natural event that specifies the length of each run. 160 years seemed to be a reasonable long time to be used as a stopping rule. In pilot simulations we also checked that the use of longer time periods for T did not produce significantly different results.
[10] We set T equal to 1920 in order to allow a "warm-up period" and thus comment our results after the system has reached a steady state.

budget. Each project is modeled as a vector, with each element representing a certain feature of the project. In particular, each project is characterized by the following features: a project ID; its cost in each phase; its lead time in each phase; its attrition rate in each phase; and an index indicating the current stage a project is in. Both lead times and attrition rates are randomly assigned. As soon as projects are generated, they enter the 3-stage process described above. During a simulation run, whenever the firm's budget allows for additional investments, new projects are generated.

Projects are independent identical distributed random variables since some of their features are generated randomly. That is, we are implicitly assuming a firm's portfolio is diversified, with each project assuring a fixed return if successful. This is so since the objective of the simulation is to explore how different heuristics used to manage R&D portfolios affect R&D performance and volatility typically, and not for a specific project. The values of some of the features of the projects firms invest in are not known a priori. For instance, a firm does not know a priori whether a certain project will be either a success or a failure, or when it will fail.

The data from the pharmaceutical industry we used to set the parameters in the simulation are presented in Table 1.

**Table 1. Data used to set the parameters in the simulation.**

| | *Average Values (in each phase)* | | |
|---|---|---|---|
| | **Phase I** | **Phase II** | **Phase III** |
| **Attrition Rate** | 60 % | 50 % | 15 % |
| **Lead Time per Phase** | 21.6 months [st dev = 6.6] | 25.7 months [st dev = 11] | 30.5 months [st dev = 9.9] |
| **Cost per Phase** | MM $ 15.2 | MM $ 23.5 | MM $ 86.3 |

* *Source*: J.A. Di Masi *et al.*, "The Price of Innovation: New Estimates of Drug Development Costs", *Journal of Health Care Economics*, 22, 2003.

*Modeling R&D project portfolio heuristics*

We focused on two types of heuristics. First, we examined how resource prioritization heuristics (holding constant scale) across the development stages impacted R&D performance. Second, holding constant resource prioritization rules and scale, we investigated the impact of project termination heuristics on R&D performance. In each simulation run, the heuristic employed by a firm remains the same in every time period. This allows the possibility for feedback loops to emerge and to reinforce the impact of a certain heuristic on R&D performance. We describe how we modeled R&D project portfolio heuristics next.

*Resource prioritization heuristics*

There are two main common resource prioritization heuristics we have observed in practice, which tend to be driven by whether the firm's main focus is exploration or exploitation (see March, 1991). A long tradition of research suggests that these are competing strategies for three reasons. First, exploitation strategies tend to limit the amount of firm exploration and exploration strategies tend to limit the amount of firm exploitation (e.g., March, 1991). Second, exploitation and exploration strategies often compete for limited resources within the firm and are associated with opposite organizational structures and cultures. Firms that pursue both strategies are viewed as lacking focus and internal fit (e.g., Miller and Friesen, 1986). Third, firms should utilize only one of these strategies to optimize their fit with the external environment (e.g., Galbraith, 1973; Lawrence and Lorsch, 1967).

If a firm is focused on exploitation it will tend to fund later stage development projects first. That is, projects closer to the market get first dibs on resources, and prioritization declines as projects move further back in the "pipeline". In our simulation model we implemented this heuristic as follows: the firm always spends resources on the latest phase projects first (i.e., projects waiting in the buffer between phase II and phase III), the second to latest phase projects second (i.e., projects waiting in the buffer between phase I and phase II) and, if some resources are left, it can also start one or more new projects. We refer to this heuristic as rule 3-2-1.[11]

Instead, if a firm is focused on exploration it will tend to dedicate resources to start new projects more frequently. In our simulation model we implemented this heuristic as rule 1-2-3, according to which the firm spends resources on new projects first, then on projects waiting in the first buffer, and finally on projects waiting in the second buffer. In particular, a firm can invest in new projects every 3 months.[12] If this was not the case, the firm would not have enough resources to move projects forward in the process and thus no output would be observed. The 1-2-3 heuristic is similar to the implicit rule used by many small, science-oriented start-up companies. They get "excited" about the new projects, while later phase projects get implicitly discounted.[13]

Various organizational factors influence the implicit or explicit resource prioritization heuristics in place. Organizational culture and history may play a critical role. For instance, a company founded by academic scientists may have a bias toward funding earlier stage research projects. At one biotechnology company we interviewed, one of the senior managers noted that for many years the company had difficulty advancing projects further into the development process because the organizational culture (heavily influenced by the academic origins of the company) emphasized early stage research. For companies similar to this one, new projects look always better than ongoing projects, based on the fact they seem promising. In contrast, at the

[11] Thus, "3" refers to the buffer between phase II and phase III, "2" refers to the buffer between phase I and phase II, while "1" refers to investments in new project. There is no cost associated with projects waiting in buffers. Moreover, we assume there are no capacity constraints for buffers.
[12] The nature and significance of the results do not change if firms can invest in new projects every 4 or 6 months.
[13] Similarly, rule 1-2-3 is often used by scholars in allocating their time to research projects.

other end of the spectrum, there are companies with very strong sales and marketing organizations that tend to exert a strong pull on resources devoted to advertising or incremental improvements in existing products. The other factors that can influence resource prioritization have to do with the firm's time horizon. A company in a difficult financial position or facing serious short-term cash issues might choose to focus its resources on products closer to market. In contrast, a firm in a stronger financial position might be able to afford to initiate more new projects that will not be ready for the market until several years out.

*Project termination heuristics*

Termination of projects is a difficult subject because of several reasons, ranging from people's tendency to procrastinate (O'Donoghue and Rabin, 1999a; 1999b; 2001) and organizational inertia (Hannan and Freeman, 1984), to political repercussions on the laboratory (Balachandra, Brockhoff and Pearson, 1996).[14] For instance, the decision to terminate a project might demoralize project managers and team members, and increase concerns about job security (Balachandra *et al.*, 1996). For these reasons, managers often tend to let projects continue and delay project termination decisions even if this might divert scarce R&D resources from higher potential projects.

In the model used to determine the impact of scale and the effect of priority rules on R&D performance, projects move through the 3-stage process "passively". They have a certain probability of success for each phase and they either succeed or not. In reality, firms make judgments about which projects move forward based on incomplete data. In the simulations

[14] Procrastination is the tendency to postpone tasks repeatedly over time. As Akerlof (1991) described it, "Procrastination occurs when present costs are unduly salient in comparison with future costs, leading individuals to postpone tasks until tomorrow without foreseeing that when tomorrow comes, the required action will be delayed yet again" (p. 1)

investigating the impact of project termination heuristics on R&D performance, these judgments are modeled as decisions made based on threshold for advancing projects. In these simulations, when a project is generated, it is labeled randomly as either a “winner” or a “loser”. The probability of obtaining a winner in each random draw is equal to 17%, which is the percentage of the projects entering clinical development that eventually result in a marketed product (DiMasi *et al.*, 2003). At each phase, and without knowing if the project is a winner or a loser, the firm must decide whether to advance or kill the project, based on data generated during the phase. Data take on the value of either 0 or 1, to indicate failure and success respectively. If the project was originally a winner, then the firm receives a signal, which is equal to an increment in the probability of getting a winner in the data generated during the phase.

We distinguish between firms which are impatient in their project termination decisions and thus tend to kill projects earlier in the development process, and firms which tend to procrastinate their project termination decisions and thus tend to kill projects later in the development process. Firms which are “tough” at the early stages and only advance projects with very strong ex-ante prospects for success are said to be using a kill early heuristic. In contrast, firms which set low bars on evidence for advancing projects forward early in the development process and higher thresholds later are said to be using a kill late heuristic.

Table 2 provides the values for thresholds that were used in the simulations for these two project termination heuristics.

**Table 2. Project termination heuristics.**

| | *Values for (ex-ante) thresholds used in each phase* | | |
|---|---|---|---|
| | **Phase I** | **Phase II** | **Phase III** |
| **Kill Late Heuristic** | 20 % | 50 % | 58.5 % |
| **Kill Early Heuristic** | 65.2 % | 50 % | 2.25 % |

Thus, for instance, a firm using a kill early heuristic might advance a project from phase I to phase II only if the probability of success is higher than 65.2%. A firm using a kill late heuristic, instead, might advance a project from phase I to phase II only if the probability of success is higher than 20%. In essence, a project progresses only if its probability of success is higher than the threshold, the threshold being the attrition rate.

## V. Analysis

We present our analysis by describing the results for small, medium and large firms. Small firms are companies with an initial portfolio consisting of 5 projects. For medium firms, the initial portfolio consists of 50 projects, while for large firms it consists of 100.

### *The Effects of Resource Prioritization*

There is a long literature on resource allocation processes going back to Bower (1970). In general, this literature emphasizes that heuristics play a key role in resource allocation decisions. Strategies like "we will not invest in projects that do not have an expected return above our weighted average cost of capital" would be an example of a heuristic that plays an important role in capital budgeting decisions. In R&D, there are various decision heuristics that influence allocation of resources to specific projects. Our field work conducted in the pharmaceutical industry suggests that one of the issues causing the most tension within companies is the prioritization of resources across stages of the development cycle (e.g. research vs. development vs. commercialization). This appears to be most pronounced when specific stages of the R&D process are the responsibility of distinct sub-groups within the organization ("Research", "Development", "Sales & Marketing"). Given that organizations tend to pursue a larger number of projects than they have the resources to fund (Wheelwright and Clark, 1992), prioritization across stages can become a source of intra-organizational conflict with each group vying to have their projects funded first.

Figure 3 shows the effect of the modeled resource prioritization heuristics on R&D output. Rule 3-2-1 leads to the highest output. Results are consistent across different portfolio sizes. For small portfolios, the mean R&D output is equal to 0.087 (SD=.132) for firms using a 3-2-1 heuristic and to 0.002 (SD=.009) for firms using a 1-2-3 heuristic, and this difference is statistically significant ($t$=6.436, p<.0001). For medium portfolios, the mean R&D output is equal to 1.617 (SD=.206) for firms using a 3-2-1 heuristic and to 1.029 (SD=.217) for firms using a 1-2-3 heuristic, $t$=19.675, p<.0001. Finally, for large portfolios, the mean R&D output is equal to 3.191 (SD=.271) for firms using a 3-2-1 heuristic and to 3.119 (SD=.336) for firms using a 1-2-3 heuristic, $t$=1.668, p=.09.[15]

Rule 3-2-1 also leads to the lowest volatility, as shown in Figure 4. For small portfolios, the mean R&D volatility is lower for firms using a 3-2-1 heuristic (M=1.938, SD=.132) than for firms using a 1-2-3 heuristic (M=4.359, SD=.001), $t$=-5.532, p<.0001. For medium portfolios, the mean R&D volatility is equal to .765 (SD=.126) for firms using a 3-2-1 heuristic and to .872 (SD=.173) for firms using a 1-2-3 heuristic, $t$=-4.979, p<.0001. Finally, for large portfolios, the mean R&D volatility is equal to .494 (SD=.070) for firms using a 3-2-1 heuristic and to.550 (SD=.089) for firms using a 1-2-3 heuristic, $t$=4.876, p<.0001.

These results suggest that firms need to focus more of their resources on later stage projects rather than new projects, even if this may run counter to their “science” driven culture, present especially in small firms. To investigate the factors driving these results we looked at the

[15] Note that for a large portfolio consisting of 95 projects, the mean R&D output is equal to 3.058 (SD=.282) for firms using a 3-2-1 heuristic and to 2.927 (SD=.341) for firms using a 1-2-3 heuristic, $t$=2.972, p=.003.

number of projects in each development phase and in the buffers for the resource prioritization heuristics considered, and their volatility. As Table 3 shows, both in phase I and II the number of projects is lower for firms using a 3-2-1 heuristics than for firms using a 1-2-3 heuristics, while the opposite is true in phase III. Also, firms using a 3-2-1 heuristic have fewer inventories than firms using a 1-2-3 heuristic. All these differences are statistically significant (see Table 3).[16]

**Table 3. Pipeline for different resource prioritization heuristics (Medium size firms).**

| | Phase I | Buffer 1 | Phase II | Buffer II | Phase III |
|---|---|---|---|---|---|
| **3-2-1 Heuristic** | 17.79 | 0.13 | 8.40 | 0.65 | 4.96 |
| **1-2-3 Heuristic** | 22.17 | 0.39 | 10.69 | 47.49 | 3.13 |
| **t-statistic (p-value)** | -19.7 (p<.0001) | -17.361 (p<.0001) | -19.51 (p<.0001) | -65.746 (p<.0001) | 23.473 (p<.0001) |

Thus, with the 3-2-1 heuristics, the distribution of projects in the pipeline is such that projects tend not to wait in the buffer between phase II and phase III and overall the pipeline seems to be "balanced". Early stage projects tend not to get "starved" for resources and late stage projects tend to get what they need. With the 1-2-3 heuristic, instead, the firm focuses on feeding the system, since resources are allocated to new projects and early phase first. Projects progress at a lower pace within the pipeline and they often have to wait in the buffer between phase II and III until enough resources become available.

We ran a regression with R&D output as dependent variable and with the following explanatory variables: number of projects in phase I, number of projects in phase II, number of projects in phase III, number of projects in buffer I, number of projects in buffer II. We controlled for both resource prioritization heuristics and firm effect. The results show that two

[16] The values reported in the table refer to the case of medium portfolios. However, the nature and significance of the results do not change for small and large portfolios.

coefficients are statistically significant: number of projects in phase I (coefficient =-.121; *t*=2.651; p=.009) and number of projects in phase II (coefficient =-.156; *t*=-2.894; p=.004).[17] Thus, the higher the number of projects in phase I and II, the lower the overall output.

Table 4 reports the volatility of projects in the pipeline for each resource allocation heuristic. As the table shows, in phase I, II and III the volatility of projects is lower for firms using a 3-2-1 heuristics than for firms using a 1-2-3 heuristics, while the opposite is true for the volatility of projects in the two buffers.[18]

**Table 4. Volatility of projects in the pipeline for different resource prioritization heuristics.**

| | **Phase I** | **Buffer 1** | **Phase II** | **Buffer II** | **Phase III** |
|---|---|---|---|---|---|
| **3-2-1 Heuristic** | 0.35 | 1.71 | 0.36 | 1.31 | 0.37 |
| **1-2-3 Heuristic** | 0.16 | 1.05 | 0.24 | 0.04 | 0.36 |
| **t-statistic (p-value)** | 22.836 (p<.0001) | 16.735 (p<.0001) | 10.801 (p<.0001) | 50.486 (p<.0001) | .245 (*ns*) |

We ran a regression with volatility in R&D output as dependent variable and with the following explanatory variables: volatility in number of projects in phase I, volatility in number of projects in phase II, volatility in number of projects in phase III, volatility in number of projects in buffer I, volatility in number of projects in buffer II. As we did in the previous regression, we controlled for both resource prioritization heuristics and firm effect. We found that two coefficients are statistically significant: volatility in phase II (coefficient =-.250; *t*=-1.945; p=.053) and volatility in phase III (coefficient =.721; *t*=6.961; p=.0001).[19] Thus, the higher the volatility in phase III and the lower the volatility in phase II, the higher the overall volatility.

[17] The R square of the regression model was equal to= .901, while the adjusted R square was equal to .847.
[18] The values reported in the table refer to the case of medium portfolios. However, the nature and significance of the results do not change for small and large portfolios.
[19] The R square of the regression model was equal to= .582, while the adjusted R square was equal to .352.

*The Effects of Project termination Heuristics*

Different organizations are likely to have different preferences for risk. One of the chief ways that risk preferences are revealed is through the criteria used to decide which projects move forward in development and which ones are terminated. For instance, Guedj and Scharfstein (2004) have documented significant variation in the rates at which biotechnology firms terminate cancer drug programs at early phases in the process. Some firms appear to have a preference for "weeding out" projects at an earlier phase, while others appear to be more willing to take comparable projects deeper into the process.[20]

Figure 5 and 6 show the impact of project termination heuristics on R&D output and volatility respectively. The kill early heuristic leads to higher output and also to lower volatility compared to the other modeled heuristic. Thus, similar to the results we obtained when varying resource prioritization heuristics, also in the case of project termination heuristics, firms do not face a tradeoff between output and volatility: by changing the heuristic used in project termination decisions, a firm can assure a higher output and lower volatility at the same time.[21] These results are consistent across different portfolio sizes. For small portfolios, the mean R&D output is higher for firms using a kill early heuristic (M=.04, SD=.07) than for firms using a kill late heuristic (M=.02, SD=.05), $t$=1.604, *ns*.[22] As for R&D volatility, it is lower for firms using a kill early heuristic (M=3.03, SD=1.00) than for firms using a kill late heuristic (M=3.55, SD=.92), $t$=-2.042, p=.046. For medium portfolios, the mean R&D output is equal to .65 (SD=.18) for firms using a kill early heuristic and to .40 (SD=.15) for firms using a kill late

[20] Guedj and Scharfstein (2004) demonstrate that these differences are related to differences in the firm's financial prospects and alternative development opportunities. Firms with weaker financial prospects and more limited development options appear to be willing to advance their programs into later stages of the development process.
[21] Notice that at each point in time the available budget is entirely spent on projects at different stages of development. Rarely, available budget remain not invested.
[22] Note that for a small portfolio consisting of 10 projects, the mean R&D output is higher for firms using a kill early heuristic (M=.13, SD=.09) than for firms using a kill late heuristic (M=.08, SD=.06), and this difference is statistically significant ($t$=4.385, p<.0001).

heuristic, *t*=10.390, p<.0001. As for R&D volatility, it is lower for firms using a kill early heuristic (M=1.20, SD=.27) than for firms using a kill late heuristic (M=1.64, SD=.56), *t*=-7.141, p<.0001. Finally, for large portfolios, the mean R&D output is equal to 1.22 (SD=.23) for firms using a kill early heuristic and to .81 (SD=.19) for firms using a kill late heuristic, *t*=13.578, p<.0001. And R&D volatility is lower for firms using a kill early heuristic (M=.89, SD=.16) than for firms using a kill late heuristic (M=1.10, SD=.20), *t*=-8.347, p<.0001.

These results suggest that firms need to be "tougher" on earlier stages of the development process rather than procrastinate their project termination decisions. To investigate the factors driving these results we looked at the number of projects in the pipeline and the in the buffers for each project termination heuristic, and their volatility. As Table 5 shows, both in phase II and III the number of projects is lower for firms using a kill early heuristic than for firms using a kill late heuristics, while the opposite is true in phase I. Also, firms using a kill early heuristic have fewer inventories than firms using a kill late heuristic. All these differences are statistically significant (see Table 5).[23] In essence, the "balance" in the firm's pipeline seems to differ based on project termination heuristics. A rule that tends to set high bars for stopping projects moving from phase I to phase II results in a front-loaded pipeline. Instead, a rule that tends to set high bars for stopping projects moving from phase II to phase III results in a back-loaded pipeline.

**Table 5. Pipeline for different project termination heuristics (Medium size firms).**

| | Phase I | Buffer 1 | Phase II | Buffer II | Phase III |
|---|---|---|---|---|---|
| **Kill Early Heuristic** | 17.62 | 0.13 | 8.00 | 0.70 | 5.13 |
| **Kill Late Heuristic** | 10.12 | 0.44 | 10.18 | 2.16 | 6.53 |
| **t-statistic**<br>**(p-value)** | 38.700<br>(p<.0001) | -16.554<br>(p<.0001) | -20.316<br>(p<.0001) | -14.173<br>(p<.0001) | -20.216<br>(p<.0001) |

[23] The values reported in the table refer to the case of medium portfolios. However, the nature and significance of the results do not change for small and large portfolios.

We also ran a regression with R&D output as dependent variable and with the following explanatory variables: number of projects in phase I, number of projects in phase II, number of projects in phase III, number of projects in buffer I, number of projects in buffer II. We controlled for both project termination heuristics and firm effect. The results show that three coefficients are statistically significant: number of projects in phase I (coefficient =-.386; *t*=-2.673; p=.009), number of projects in phase II (coefficient = -.467; *t*=-2.635; p=.010) and number of projects in phase III (coefficient =-.1.315; *t* =-2.476; p=.015).[24] Thus, the higher the number of projects in progress in phases I, II and III, the lower the overall output.

Table 6 reports the volatility of projects in the pipeline for each project termination heuristic. As the table shows, in phase I and II the volatility of projects is lower for firms using a kill early heuristic than for firms using a kill late heuristic, while the opposite is true for the volatility of projects in the two buffers and in phase III.

**Table 6. Volatility of projects in the pipeline for different project termination heuristics.**

| | Phase I | Buffer 1 | Phase II | Buffer II | Phase III |
|---|---|---|---|---|---|
| **Kill Early Heuristic** | 0.35 | 1.71 | 0.36 | 1.21 | 0.35 |
| **Kill Late Heuristic** | 0.51 | 1.45 | 0.40 | 0.98 | 0.28 |
| **t-statistic (p-value)** | -12.235 (p<.0001) | 5.247 (p<.0001) | -3.081 (p=.002) | 8.776 (p<.0001) | 6.398 (p<.0001) |

We ran a regression with volatility in R&D output as dependent variable and with the following explanatory variables: volatility in number of projects in phase I, volatility in number of projects in phase II, volatility in number of projects in phase III, volatility in number of projects in buffer I, volatility in number of projects in buffer II. We controlled for both project termination heuristics and firm effect. We found that two coefficients are statistically significant:

[24] The R square of the regression model was equal to= .720, while the adjusted R square was equal to .408.

volatility in phase II (coefficient = -.1.755; t stat = -2.089; p = .039) and volatility in phase III (coefficient =1.721; t stat = 1.805; p = .074).[25] Thus, the higher the volatility in phase III and the lower the volatility in phase II, the higher the overall volatility.

*Interaction between project termination and resource allocation heuristics*

In the simulations described in the previous section, different project termination heuristics were compared and the resource prioritization heuristic was held constant (rule 3-2-1). We conducted further simulations to study the interaction between project termination and resource prioritization heuristics. In particular, we used the two project termination heuristics explored above in the case of a 3-2-1 priority rule versus the case of a 1-2-3 priority rule. Overall, the analyses conducted show that using a kill early heuristic is a dominant strategy whether the firm is using rule 3-2-1 or rule 1-2-3 to allocate its resources.

*Robustness of the results for the effects of project termination and resource allocation heuristics*

In the simulations described in the previous sections, we assumed that every time budget was available and the firm decided to use it for investments in new projects, projects were available. That is, we assumed that firms have full capabilities in discovery. We conducted further simulations to check whether results hold in the case of limited capabilities in discovery. In particular, we used two different values for "capabilities in discovery": when a firm can invest in new projects, a project is available with a probability of either 50 or 20%. Overall, the analyses conducted show that results and their significance do not change if different values for capabilities in discovery are used.

[25] The R square of the regression model was equal to= .599, while the adjusted R square was equal to .151.

## VI. Conclusions and Implications

In this paper we have explored the impact of R&D project portfolio management heuristics on performance volatility over time at the firm level. We modeled a 3-stage R&D process. Such a process characterizes most of the modern companies if we think of phase I as research, of phase II as development, and of phase III as commercialization. We referred specifically to pharmaceuticals. Our model can be easily extended to consider post-launch investment decisions and their ramifications for volatility. In addition, our model can be extended to consider decisions about investments in products at different stages of their life cycle (e.g., "next generation" technology (high uncertainty) versus incremental investments in improving the current technology). Moreover, settings with different cost and lead time structures can be explored by varying the simulation parameters.

Although our model was focused on a narrow set of management heuristics, it does have some potentially interesting implications for industry structure and funding strategies. Specifically, while the 3-2-1 allocation heuristic appears to be dominant at the firm level, it is entirely possible for the external funding environment (i.e. the capital markets) to influence to alter the priorities at the industry level. For instance, in the late 1990s, amidst a high level of excitement concerning genomics and other new technologies, venture capital funding appeared to favor companies with early stage projects. In essence, at an industry level, there was a kind of 1-2-3 allocation rule at work. While further simulation analysis is needed at the industry level, our current model analysis suggests that such a funding environment could contribute to volatility in R&D output (at the industry level) over the long term. In addition, our results suggest that to the extent that a combination of capital market imperfections and principle agent problems may lead some firms to adopt "risk seeking" behaviors with a tendency to kill project late in the development process (see, for example, Guedj and Scharfstein, 2004), a greater level of R&D volatility could be expected.

The limits of the present paper suggest several lines of future research. First, in terms of future simulation work, it would helpful to explore a broader range of R&D contexts with structurally different uncertainty. For instance, one might compare how the dominant heuristics vary with changes in the nature of attrition uncertainty, lead time uncertainty, and development costs. The current model could also be enriched by considering the possibility of in-licensing, learning the effects of experience, and the possibility that successes (failures) are correlated within clusters of technological related projects (e.g. projects in similar therapeutic categories). Finally, we need to stress that while simulation is useful for exploring specific effects in a controlled manner, we have lost some of the richness of an empirical setting. We hope that this paper has highlighted some fruitful avenues for further empirical validation and exploration.

**Figure 3. Impact of Resource Prioritization Heuristics on R&D Output.**

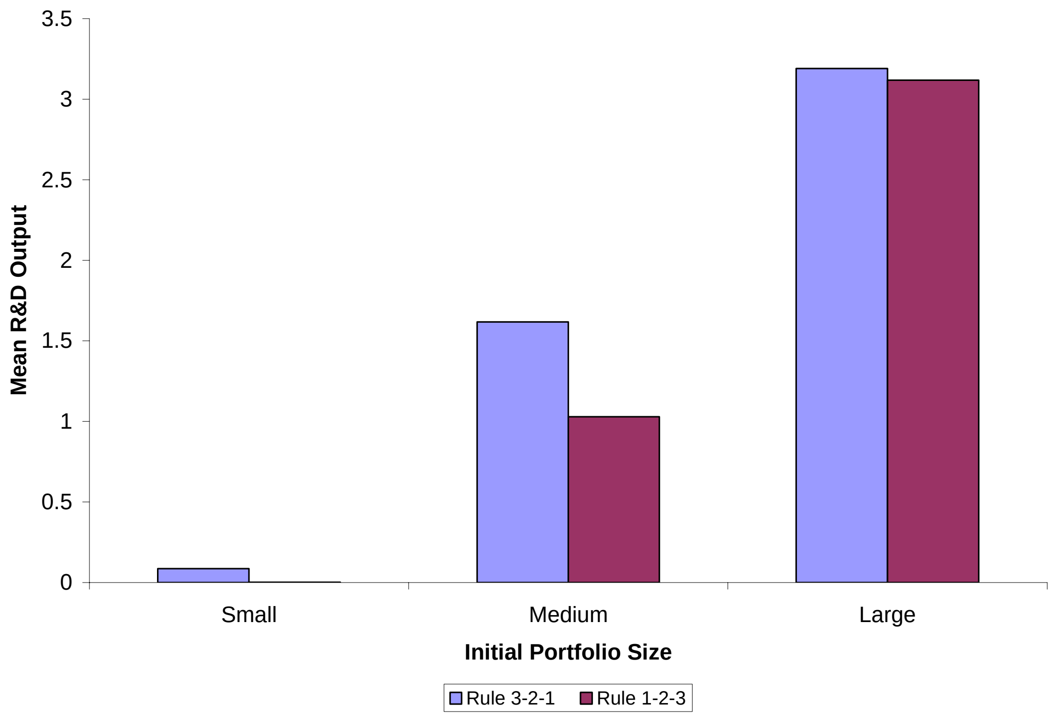



**Figure 4. Impact of Resource Prioritization Heuristics on R&D Output Volatility.**

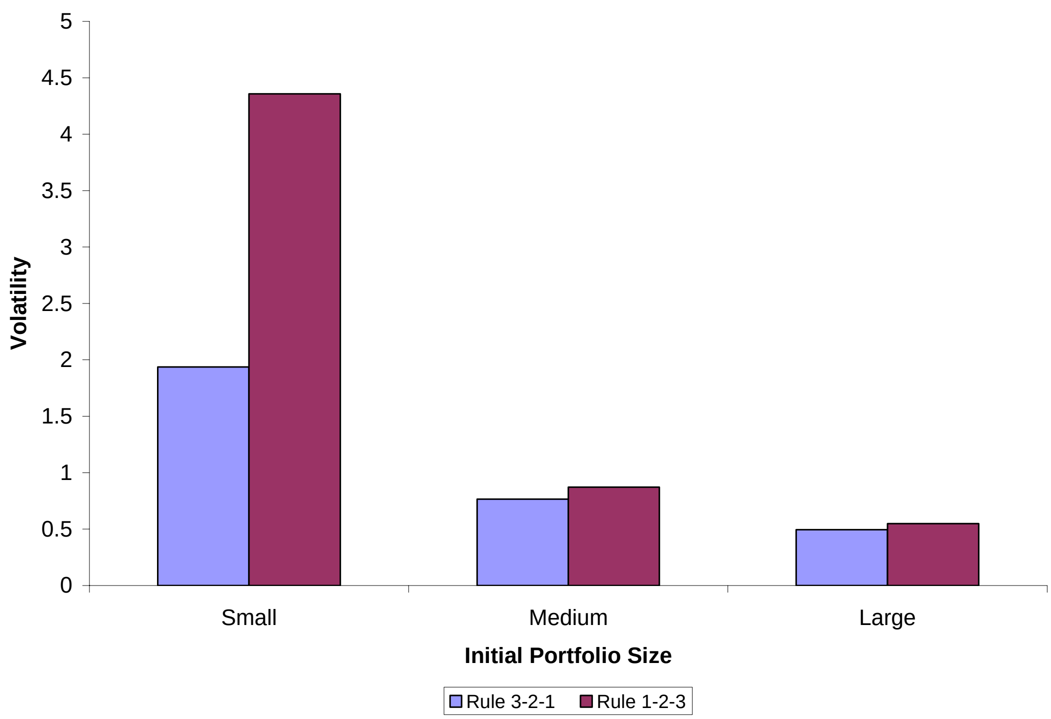


**Figure 5. Impact of Project Termination Heuristics on R&D Output.**

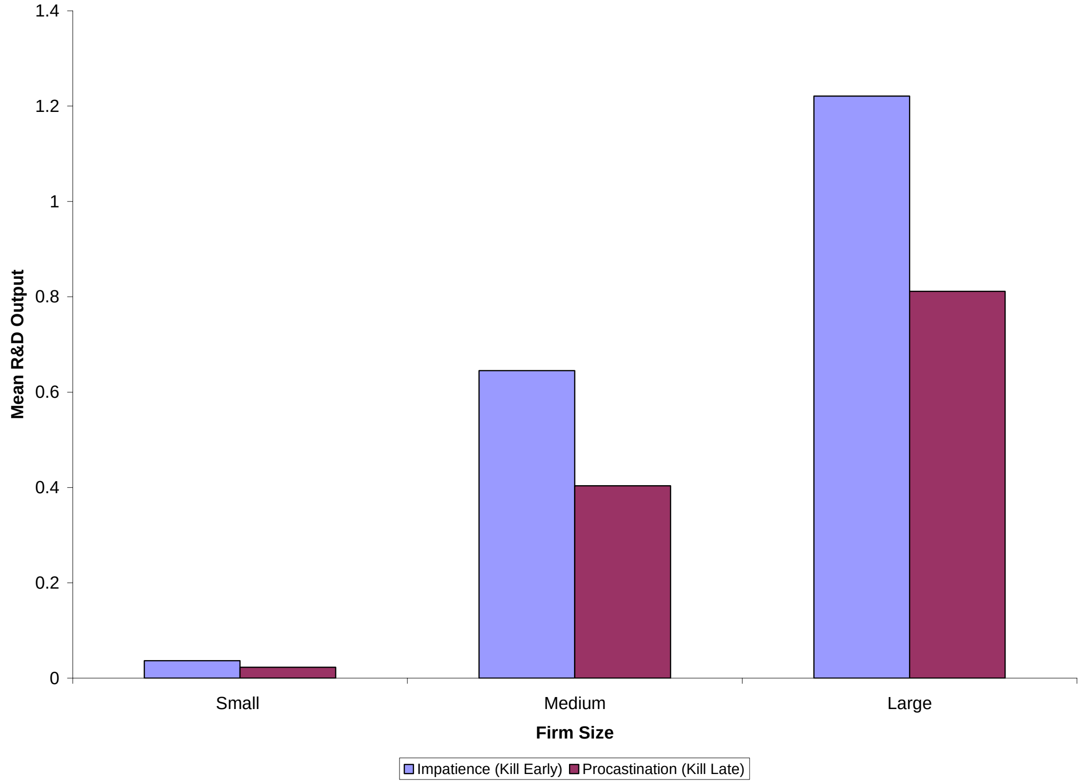
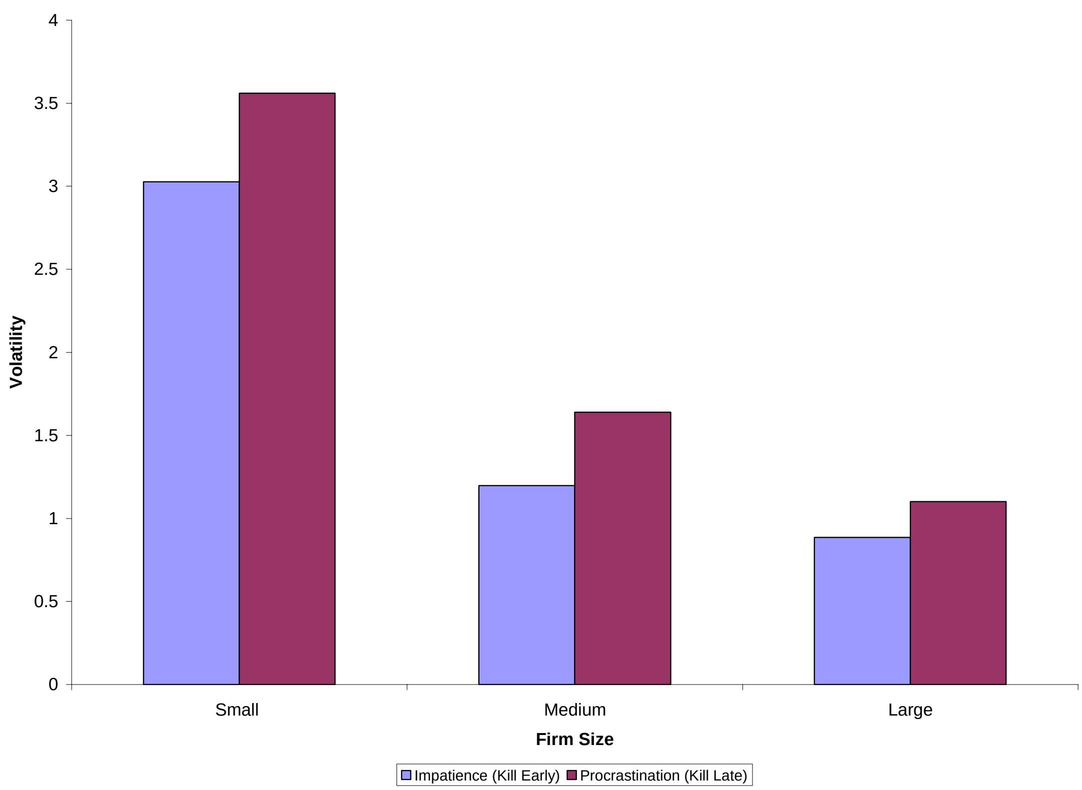



**Figure 6. Impact of Project Termination Heuristics on R&D Output Volatility.**



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