Comparing Decision-Making in R&D:
A Process Approach

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Comparing Decision-Making in R&D: A Process Approach

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Abstract
This paper presents results of a comparative study of innovation decision-making in multinational companies. A set of R&D projects is analyzed at matched pairs of Dutch and American chemical and food company sites, obtaining practical results on the management of corporate R&D. Econometric techniques are used to analyze the dynamic allocation of efforts in various R&D contexts.

JEL classification: O31; D21; L23;

1. Introduction

Economics is about making decisions. Nevertheless, economic theory seldom studies *the process* by which decisions are made. As a rule, we start from the assumption that the process of decision-making is impersonal, objective, and independent of the context. We allow the context to influence *decision outcomes*, but we do not allow it to influence the process by which the decision is made.

Processes and procedures of decision-making do differ across environments and situations. This has extensively been shown across the social sciences. Management scholars, sociologists and psychologists have uncovered systematic processes of decision-making (see e.g. Allison (1971), Hickson et al (1986)). Given these advances, economic theory should change. Behavioural theories of the firm (e.g. Cyert and March (1963), Nelson and Winter (1982)) have captured some of the key aspects of the decision-making process into economic thinking about firms, but the adoption of these theories is still limited. Economic theory seems incomplete if the context-dependence and dynamics of the effective processes of decision-making are ignored.

This paper presents results of a comparative study of innovation decision-making in multinational companies. The focus is on decision-making with respect to allocation of efforts in R&D. We show that the context-dependence of R&D decision-making entails that companies should make more conscious decisions as to where to execute which type of R&D activities. The practice of local decision-making appears to create circumstances that are suitable for specific types of R&D. Therefore, the MNE may need to fine-tune its R&D efforts, both on a micro and macro level.

The rest of this paper consists of four parts, treating the research design, the analytical model, its operationalization, empirical results and the policy implications. An appendix provides some background on the econometrics, the estimation routine and the data[1].

2. Research Design

Figure 1 depicts the concept of comparison. We study Dutch and American companies with sites in the US and the Netherlands. Each 'ball' represents a site, at which we analyze several R&D projects.

Figure 1 Research Design: Pair Companies

We focus on two industries, chemicals and food, two countries of operation, the Netherlands and the US, and two countries of origin, also the Netherlands and the US. This gives us two

[1] For the complete analysis, and the extensive description of this research project, one is referred to Meijaard (1998). The results presented in this paper are only one of the three perspectives that the author has taken to analyze the manifestation of R&D decision-making processes in various contexts. The other two perspectives focus on the

quartets of sites, eight sites in total. At each of the sites, we investigate two to four R&D projects. Across industries, countries of operation, countries of origin and corporate positions, we analyze similarities[2]. Of primary interest are *the dynamics of the research and development process*. We focus on decision-making in the process from idea to implementation in twenty-seven similar R&D projects.

Figure 2 shows the essence of R&D decision-making as we analyze it. An *innovation* is the ***set** of alternatives under consideration.* The (expected) economic environment determines the R&D decision-making process. The internal organization of the firm and feedback from other projects are critical as well. Conditional on available information about these determining factors, decision-makers choose to execute, redesign, stop or postpone further R&D. New efforts lead to new decision-making moments, and typically choices reoccur at a number of stages of any R&D project. As mentioned, the dynamic environment is very important to each of these interim R&D decisions.

Figure 2 Research Design: Innovation Decision-Making

context level

project level

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group decision-making process and on the systematic patterns of progress within the R&D projects. See also Meijaard (1999b and 1999c).

2 The eight sites consist of sites in the US and the Netherlands for Akzo Nobel (A) and Dow Chemical (D) [chemicals] and Unilever (U) and H.J. Heinz (H) [foods]. As shown, our sample of sites can be viewed as a cube from which '*slices*' are contrasted. Slices consist of a quartet of sites along a particular dimension, e.g. all chemical sites, all sites in the Netherlands or all sites of American firms.

3. Model

For each project, we distinguish six typical R&D phases. These phases serve as the structural basis for our empirical investigations. Each of the consecutive phases is involved with making decisions based on information about past and future developments. In between decisions, information is gathered. Each project consists of phase 0 ("trigger phase", first idea + gestation), phase 1 ("identification phase", definition + first plan), phase 2 ("development phase", several alternatives), phase 3 ("focused development phase", few alternatives), phase 4 ("optimization phase", preparation), and phase 5 ("implementation phase", transfer to operations and the market). *The phasing is not linear*. For various reasons, many projects experience re-iterations of phases[3]. We take explicit account of this, by comparing the specific phases to each other. The iterated phases are combined and checked for oddities.

At the start of phase 1, *seed capital* is allocated to the innovation in order to develop an initial concept. The decision-makers determine the amount of time and money α_1 that is to be spent on the identification of the innnovation opportunities. These efforts are allocated based on initial knowledge I_1 about the project:

(1)

$D_1^A(\ )$ is a rule by which it is determined how much time and resources (α_1) will be spent to develop a more detailed concept I_2 of the relevant alternatives and the steps in the research and development process. It is based on the (long term) performance forecasts $\pi_1^e(\ )$, which in turn is based on the initial information set I_1.

The set I_1 contains the information about the innovation's opportunities and prospects, that are known before research and development starts. Typically, the critical features of the innovation have been attributed an initial value. The information set is defined as:

(2)

m_1 = market information,
c_1 = costs and characteristics,
o_1 = organizational fit

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[3] Induced by competitive, organizational or technological changes, unexpected discontinuities may occur. Irrespective of such reloops in R&D progress, projects can be viewed to consist of a set of comparable phases. In each phase, information is gathered and processed in a particular way. In the end, the sequence of R&D efforts co-determines the manifestation of innovations, and the route to implementation has similar features across innovation projects.

Each of these three information sets consists of a (subjective) probability distribution for a category of features. These probability distributions are assumed to summarize the decision-makers' beliefs about the innovation features are and the way in which they might evolve. These are denoted x_{ijk}. The three probability density functions reflect critical expectations about the comparative merits of the innovation (profits, uncertainties, life time)[4]:

$$
\begin{aligned}
&m_1 = m_1\,(x_{111}, x_{112}, x_{113}, ...)\\
(3)\qquad &c_1 = c_1\,(x_{121}, x_{122}, x_{123}, ...)\\
&o_1 = o_1\,(x_{131}, x_{132}, x_{133}, ...)
\end{aligned}
$$

Based on this information set I_1, the overall expected performance $\pi_1^e(\ )$ can be assessed, determining the choice D_1^A. The performance is a summary of the essence of the prosepcts regarding the innovation, e.g. profitability (costs, benefits, duration), stability (risks) and uncertainty. $\pi_1^e(\ )$ can best be viewed as the economic future of the innovation, paying explicit attention to the importance of the technological, market and organizational features.

Evaluation of the expected performance generates information about the expected relevant time period, about the expected improvement of overall performance to the company (the expected pay-off path relative to the operations to be replaced) and about the uncertainties that are involved. This expected performance is given by:

$$(4)\quad \pi_1^e(I_1) = \qquad\qquad\qquad\qquad (\qquad\qquad)$$

Risks are assumed to be accounted for in these performance expectations by means of the scenarios probabilities (q_{st}), which weigh the calculation of π_1^e. The p_t are prices, q_t quantities, and c_t costs, as expected per period of future returns. The relevant time T is determined by the total of the sum compared to the sum of benchmarks π_t-bar. $\pi_1^e(I_1)$ fully determines the choice D_1^A.

As well, the expected performance defines a vector W_1^e of weights w_{1j}. This reflects the importance of the three research fields to the performance assessment at each decision node. The weights will be used to determine the time and efforts to be expended per field of particular research in the development of the concept I_2.

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[4] These joint probability distributions may be very degenerate, especially at this first decision node. Many elements in the functions have trivial estimates and associated probabilities, especially at this first node of decision making.

(5) $\{w_{11}, w_{12}, w_{13}\} = W_1^e(\pi_1^e) =$

W_1^e indicates the relative importance the decision-makers at this first decision of the first node attribute to the fields of research. It represents the estimated long-term effects of the characteristics of the individual fields.

We will assume that each field of research provides crucial inputs to the performance assessment π_1^e. The objective of the research activity (during the first phase) will be to revise (in a Bayesian manner) the prior knowledge I_1 into an improved knowledge I_2. α_1 is distributed over the three research fields, improving knowledge as best as possible (a priori).

The *effectiveness* of the investment α_1 made into this activity, $R_1(I_2|I_1,\alpha_1)$, depends on the capabilities of the R&D team to improve the information about the new project. This R_1 is the conditional probability distribution of (*posterior*) knowledge I_2 given initial (*prior*) knowledge I_1 and seed capital α_1. Actually, R_1 is a *vector* of the three joint conditional probability distributions of the posterior knowledge about the individual variables m_2, c_2, o_2: $(r_{11}(m_2|m_1,\alpha_{11}), r_{12}(c_2|c_1,\alpha_{12}), r_{13}(o_2|o_1,\alpha_{13}))$, given initial knowledge I_1 as in equation (2) and capital allocations α_{1j} to the specific research fields.

The α_{1j}'s are the resources to be spent in phase 1 per research field. They are the solution to a second allocation problem D_1^B at the first node. This is based on the expected knowledge improvements during the first phase of research on the innovation:

(6) $r_{1j}(j_2|\, j_1, \alpha_{1j}) - j_1$ with j = m, c, o (corresponding to 1,2,3)

The allocation of individual field resources $\{\alpha_{1j}\}$ is determined by solving D_1^B:

(7) s.t.

with $\{w_{1j}\}$, as determined by (5). It should be stressed that we assume these weights to be predetermined or exogenous to this second decision problem D_1^B. They are defined along with π_1^e. In practice solutions to D_1^B are found by rules analogous to knapsack problem solving.

The allocations (α_{1j}} are actually spent on investigations per field by a third decision making procedures D_{1j}^C that cannot be generalized. This fully depends on the actual innovation contents e empirical research will have to shed light on their contents. The efforts during the phase in improved knowledge I_2 on the market m_2 , costs c_2 , and context o_2.

This information set I_2 will be the input to the new decision D_2^A, the decision to allocate a particular amount of resources α_2 to the development of a several alternatives and an initial implementation plan. This decision is made based on expected performance $\pi_2^e(I_2)$ (analogous to D_1^A). The conditional probability distribution for the beliefs at the *third* decision node $R_2(I_3|I_2,\alpha_2)$ and the updated performance weights of the various research fields W_2^e determine the choice of distribution of efforts D_2^B in the second phase. Analogously, these efforts are again expended by decision making procedures D_{2j}^C, now in order to develop I_3, the information set based on which the decision will be made to further develop and/or design the innovation. These decision-making processes continue until phase 5.

Each of the variables in the information set is only an indication of knowledge about the respective feature of the innovation *at a given moment in time.* All components, all variables, and thus all performance appraisals are static, rigid estimates of the innovation's crucial attributes. Critical to all information processing during innovation development and decision making is the synthesis and integration of features that have a similar content, weight, riskiness and uncertainty. The way the decision-makers structure their beliefs in order to arrive at a consistent appraisal of the expected performance of innovations is very important. In our study of the group decision0-making process, we focus on how they handle uncertainties and risks to attempt to minimize the bounding and often paralyzing effects of major uncertainty and risk.

After research and development of the innovation have ended, the implementation and performance are reviewed at consecutive stages in the operation of the innovation. At each of these review points additional information relevant to the learning process from the innovation may be released. Based on it we can adjust decision making and information gathering with respect to future innovations. This ex-post learning is beyond the scope of our investigations.

Summarizing, the model is based on expectations and preferences about what performance could look like. This determines the decisions at the various nodes to continue, halt, alter or stop the development of an innovation. π_i^e at any node is the expected profit path of the innovation in the future. It is a preference function, valuing the probability distribution of the flow of performance pay-offs after implementation relative to the time horizon T and uncertainties involved. This π_i^e and its components are updated at every node by using improved information I_i.

4. Operationalization

After selection of suitable projects per site, we apply a ‘standard’ fieldwork procedure. An in-depth study of documents and interviews with all key parties are synthesized into semi-quantitative data. Here, we focus on efforts, project features and time spent across R&D phases. The data are analyzed across projects and sites, searching for systematic patterns of R&D decision-making for industries, countries of operation, countries of origin and corporate positions. The reader is referred to Meijaard (1998) for full details on the field work procedures.

Figure 3 depicts the essence of the analysis: we study how project features and R&D efforts jointly determine the time spent per phase in R&D. Costs and performance are normalized, which ssems appropriate given the careful selection of projects. The relative time spent per R&D phase is used an indicator of R&D effectiveness. Of course this is not the only relevant indicator of R&D performance, but it is the most important indicator given our careful selection of cases and our focus on relative performance. The core of our analysis is the study of the dynamic evolution of R&D efforts, project features and phase duration[5].

Figure 3 Simplified static framework for analysis of the effort allocation process

[*] numbers in brackets denote the number of variables per category

Summarizing, we model and test how changes in the project features and R&D efforts determine the relative duration of R&D phases. In our study, nine project feature variables describe the decision-making situation in each of the phases of R&D.

5 The framework derives from R&D management theory (Wheelwright and Clark (1992), Roussel et al. (1991) Van de Ven et al. (1989)), combined with theory of decision making (Simon (1957), Cyert and March (1963)). Once again, full details can be found in Meijaard (1998).

The project feature variables are an operationalization of those decision features and contextual conditions that directly impact decision-making. The variables deal with uncertainty (2 variables), expectations (2 variables), structure (2 variables), priority (1 variable) and leeway (2 variables). They are listed in Box 1.

Box 1 Project feature variables

S_1	**budgetary leeway**	Budgetary discretion for the R&D efforts. The budgetary leeway concerns the financial room: Are deviations allowed?
S_2	**time leeway**	Time discretion for the R&D efforts. The time leeway concerns the strictness of timelines: Are deviations allowed?
S_3	**likelihood of success**	Likelihood of success of the project. This denotes all expectations (technical, commercial and organizational).
S_4	**technical feasibility**	Technical feasibility of the project. This denotes the technical expectations. Can it be done?
S_5	**planning detail**	Detail of planning on the project. How much are efforts structured and specifically planned
S_6	**planning rigidity**	Rigidity of planning on the project. How fixed (or flexible) is the planned structure of efforts?
S_7	**project priority**	Priority of the project to the business as a whole. This concerns the importance of the project.
S_8	**final target uncertainty (uncertainty-I)**	Uncertainty with respect to the final target of the project. This concerns clarity of goals, and transparency of expectations.
S_9	**opportunity range uncertainty (uncertainty-II)**	Uncertainty with respect to the range of opportunities. This covers relevance of alternatives, and the clarity of the domain.

The effort variables deal with handling alternatives (3 variables), updating information (3 variables), planning (1 variable), and upward referral (1 variable). All of these variables concern potentially important determinants of R&D progress (e.g. Wheelwright and Clark (1992)). All variables relate to information processing: when is information gathered and when is it discarded? Box 2 displays the eight effort variables that we use in our study, derived from the decision-making theory.

Box 2 Effort variables

E_1	**definition/framing**	Efforts expended on definition and framing of the decision topic and its alternatives: definition of the project options
E_2	**specification**	Efforts expended on increasing detail for scenarios and alternatives to the project: specification of the options
E_3	**planning**	Efforts expended on project planning and scheduling: planning of time and resources to spend in subsequent phases
E_4	**scope reduction**	Efforts expended on reduction of the scope for the project: active reduction of the number of relevant alternatives
E_5	**competition scanning**	Efforts expended on scanning competitive action: industry or national conditions for implementation may have altered
E_6	**internal context search**	Efforts expended on searching the internal company context: internal conditions for implementation may have altered
E_7	**updating expectations**	Efforts expended on refreshing the expectations about the project: updating the expectations of results and timing
E_8	**upward referral**	Upward referral concerns issues that require decision-making authority outside the directly involved project team

The analytical strategy to study the dynamic relationships between project features $S_{l,j}$, R&D efforts $E_{k,j}$, and phase duration T_j is as follows. We analyze how *changes* in efforts and changes in project features determine relative *changes* in phase duration. The change variables are denoted $s_{l,j}$, $e_{k,j}$ and t_j. Corresponding transformations are:

$s_{l,j}$	=	$S_{l,j} - S_{l,j-1}$	for $l = 1,\dots,9$ and $j = 1,\dots,5$
$e_{k,j}$	=	$E_{k,j} - E_{k,j-1}$	for $k = 1,\dots,8$ and $j = 1,\dots,5$
t_j	=	$\ln(T_j) - \ln(T_{j-1})$	for $j = 1,\dots,5$.

As explained, we have data of twenty-seven projects on six 'standard' R&D phases. Note that, after transformation, we can only work with data on five phases. Since the models below also include the lagged efforts $e_{k,j-1}$ as explanatory variables, we are only able to explain the phase duration changes in phases 2, 3, 4 and 5 of the process.

Basically, we assume the data generation process to be a dynamic process in transformed phase duration t_j. The model that we use is similar to the 'standard' panel data analysis (first described by Balestra and Nerlove (1966)). We include so-called *fixed effects* per phase and per site[6]. In vector notation, the variables are denoted as $\underline{e}_k$, $\underline{s}_l$, and $\underline{t}$. These are vectors of stacked observations across N=27 projects, ordered per site, and across J=4 phases (these are the phases *2*, *3*, *4* and *5*).

The basic regression is the following:

(1)

The left-hand term $\underline{t}$ is an NJ $\times$ 1 vector of transformed observations on phase duration: the proportional changes in time spent per project per phase.

The first right-hand term $\underline{d}$ is a NJ $\times$ 1 vector of dummy variables, one for each phase for each site. The second right-hand term $\underline{t}_{-1}$ is a NJ $\times$ 1 vector of lagged dependent variables. They are multiplied by the one-dimensional parameter b_0. The third right-hand term X is the matrix of explanatory variables. The columns of matrix X consist of the eight current effort changes $\underline{e}_k$, the eight lagged efforts changes $\underline{e}_{k,-1}$ and the nine current project feature changes $\underline{s}_l$. These give a total of K=25 explanatory variables.

[6] That is, we include different dummy variables for each phase at each site. In the standard panel data model one usually does not assume similar effects for more than one series. However, our research design with '*embedded*' units of analysis makes this point of departure the most logical. In addition to the most common panel models, we vary fixed effects across the project phases.

The matrix is multiplied by $\underline{b}$, being a $K \times 1$ vector of parameters. The $\underline{e}$ is an $NJ \times 1$ vector of error terms, assumed to be distributed $N(\underline{0}, s^2 \chi I_{NM})$. We only allow for *fixed* effects, and we assume that there is no serial correlation or heteroskedasticity in the errors (of course testing for the validity of the assumption). This means that we assume all dynamics and across-project similarities to be captured by the set of included explanatory and dummy variables.

We investigate causalities across sites, industries and countries. After recognizing that site differences are indeed important, we study various panel *slicings*. Each such slice splits the data into two sets of observations. The range of the *slices* is depicted below.

Table 1 Range of panel slices

slicings:		*slice description:*	*label*
I	**industry:**	chemical sector	c
		food sector	f
II	**country of operation:**	in the United States	US
		in the Netherlands	NL
III	**country of origin:**	'Dutch'	fus
		'American'	fnl
IV	**corporate position:**	at home	mo
		abroad	do
V	**time:**	phase 2+3	p23
		phase 4+5	p45

When we investigate a particular slice, we *ignore* the possibility of differences within its segments. For example, when studying the subsample for operations in the Netherlands (*NL*), the parameter values are assumed to be the same at *any* of the sites *A-NL*, *D-NL*, *U-NL* and *H-NL*. They are restricted to have similar coefficients $\underline{b}$ (and only the dummy effects $\underline{d}$ are allowed to vary across these sites).

The consistency within a slice will be tested on pairs of sites (*subslices*). Once we have determined a good description of the relationship between $\underline{t}$, $\underline{e}_k$, and $\underline{s}_l$, we can compare the parameter estimates of these subslices. By doing so, we derive alternative relationships for the same site. As a result, we can check the robustness of the parameter estimates, and derive a rich a array of results (see Appendix A).

5. Panel Analysis

The first analysis presented in Table 2 examines the overall relationship between efforts, project features and phase duration, leaving aside *site*- and *time*-specific causalities. For the moment, we assume that all effects of project features and R&D efforts are similar across sites and phases. This can be viewed as the analytical base case.

Investigating the results, almost 50% of the proportional changes in phase duration are corrected in the next phase[7]. This means that quick phases are generally followed by slow ones, and vice versa. Definition/framing e_1 and internal context search $e_6(-1)$ reduce phase duration. Time leeway s_2 and final target uncertainty s_8 tend to slow progress down. Furthermore, overall, the phase duration increases from phase-to-phase. *Taking these effects as given*, chemical sites in the Netherlands are quick in development and slow in implementation. Furthermore, food sites 'abroad' are *comparatively slow* in development.

Table 2 Parameter Estimates for Base Run

			sd
explanatory variables	$t(-1)$	*-0.48*	*(0.07)*
	e_1	*-0.14*	*(0.06)*
	$e_6(-1)$	*-0.18*	*(0.07)*
	s_2	*0.28*	*(0.09)*
	s_8	*0.38*	*(0.10)*
dummy variables for phases and sites	d_2	*0.51*	*(0.16)*
	(NL-c)*d_2	*-0.79*	*(0.24)*
	(do-f)*d_2	*0.72*	*(0.24)*
	d_3	*0.42*	*(0.11)*
	d_4	*0.13*	*(0.12)*
	(D-US)*d_4	*-0.78*	*(0.27)*
	d_5	*0.39*	*(0.13)*
	(NL-c)*d_5	*0.74*	*(0.24)*
outliers	$(\text{A-NL-3})_3$	*-1.49*	*(0.51)*
statistics:	No. of observations	100	
	R-squared	0.56	
	Adjusted R-squared	0.49	
	Sum squared resids.	20.0	
	Durbin-Watson stat.	2.01	
	Bera-Jarque stat.	0.04	

NL-c = chemical sites in the Netherlands
do-f = food sites abroad

[7] For each of the regressions, leaving out the correction term, has very limited impact on the sign and magnitude of the effects of the other variables. This strengthens the assumption that the model in proportional changes is the actual data generating process, that ia the correct reflection of the decision making process. Of course, it is crucial that all possible serial correlation is actually captured by the included variables.

We proceed to discuss models for the logical subsets of our data as listed in Table 1. Each pair of complementary data subsamples *('slices')* provides an alternative to the base model presented above. At the end of the section, we discuss the dominance of specific effects.

Results across Time

The *time*-slices are the first pair of subsamples that we study. In the first slice, the development phases, definition/framing efforts e_1 reduce phase duration. These efforts -aimed at clarifying the scope and the bounds of the project- pay off early on. Similarly, project progress slows down if these definition/framing efforts are being neglected in the early phases. This basically means that project definition requires attention, at least until optimization starts.

Specification efforts e_2 have a slowing effect on progress. Of course options need to be listed and valued, but progress slackens if specification detail is too large. In the implementation phases something similar applies. It immediately takes more time if details still need to be figured out.

A similar effect applies to the planning efforts e_3. Large efforts into planning correlate with slow development and slow implementation. Although common sense suggests that reduction of planning increases the risks of harmful inefficiencies, in an R&D context it is worthwhile to *limit* planning, and focus on doing (and learning).

Scope reduction efforts e_4 slow down final implematation. It seems that too often, alternative options are still left open when the best option is being prepared for implementation. This is shown to have adverse effects on the speed of implementation. As will be seen below, this effect is most striking in the Netherlands.

Early internal context search e_6 tends to benefit the progress of R&D. Projects that fail to search the internal context early run the risk of losing precious time later, particularly wasting it on updating expectations e_7. New expectations alter the course of efforts and induce additional activities.

Finally, upward referral e_8 has a siginficant effect on progress. These efforts accelerate progress in the development phases. They are often a necessary requirement for progress to further phases, directly helping to resolve ambiguity and indecisiveness as well.

Two project feature variables have a consistent effect on phase duration. Improved technical feasibility s_4 corresponds to acceleration of R&D progress. Final target uncertainty

s_8 slows progress down particularly if the uncertainty persists. Furthermore, in the implementation phases, an impact of time leeway s_2 is felt. The effect entails that freedom to spend time corresponds to time actually spent. Progress will also tend to be slow if opportunity range uncertainty s_9 persists.

It is surprising that other project feature variables do *not* have an effect. Budgetary leeway does *not* have an overall effect, nor do likelihood of success, rigidity of planning or project priority. Apparently -if relevant at all- these effects are context-dependent.

Table 3 Parameter Estimates for Time Slices: 'phase 2 and 3' vs. 'phase 4 and 5'

slice:	*phase 2 and 3*		*sd*	*phase 4 and 5*		*sd*
explanatory variables	$t(-1)$	-0.40	(0.07)	$t(-1)$	-0.52	(0.09)
	e_1	-0.38	(0.06)	e_2	0.39	(0.08)
	$e_2(-1)$	0.45	(0.08)	e_3	0.58	(0.08)
	$e_3(-1)$	0.33	(0.11)	e_4	0.20	(0.06)
	$e_6(-1)$	-0.38	(0.08)	$e_7+e_7(-1)$	0.16	(0.05)
	e_7	0.27	(0.07)	s_2	0.63	(0.09)
	e_8	-0.31	(0.09)	s_4	-0.35	(0.11)
	s_4	-0.34	(0.10)	s_8	0.70	(0.12)
	s_8	0.47	(0.11)	s_9	0.39	(0.09)
dummy variables for phases and sites	d_2	0.47	(0.13)	d_4	0.24	(0.11)
	(NL-c)*d_2	-1.16	(0.19)	(D)*d_4	-0.70	(0.18)
	(do-f)*d_2	1.18	(0.20)	(A-NL)*d_4	-1.37	(0.28)
	d_3	0.15	(0.10)	(U-US)*d_4	1.18	(0.26)
	(US-f)*d_3	-0.66	(0.22)	d_5	0.59	(0.10)
				(NL / H-NL)*d_5	1.09	(0.17)
outliers	$(\text{H-NL-2})_2$	-1.38	(0.40)			
	$(\text{A-US-1})_2$	-1.38	(0.46)			
	(A-NL-3)	-0.92	(0.28)			
statistics:	No. of observations	54		No. of observations	46	
	R-squared	0.81		R-squared	0.86	
	Adjusted R-squared	0.73		Adjusted R-squared	0.80	
	Sum squared resids	4.37		Sum squared resids	3.03	
	Durbin-Watson stat	1.61		Durbin-Watson stat	1.67	
	Bera-Jarque stat	0.55		Bera-Jarque stat	0.45	

NL-c = chemical sites in the Netherlands
US-f = food sites in the United States
do-f = food sites abroad

Results across Industries

Separating our sample of R&D projects across industries, model reduction produces the results displayed in Table 4. Firstly, *at the chemical sites*, the feedback effects of phase duration are comparatively large. Besides this, definition/framing efforts e_1 are important. Boundaries to projects apparently need to be monitored closely such that updating expectations e_7 and scope reduction e_4 have their desired effects. Early competitive scanning

e_5 is also critical. The implementation of chemical projects apparently works well under time pressure $-s_2$, *as long as* budgets s_1 suffice. In contrast to food sites, pursuing *narrow* projects is less critical (as long as the final target is clear). *At the food sites*, it seems crucial to keep the scope of projects narrow, and to keep the efforts focused. Additionally, upward referral has strong timesaving effects and project priority actually leads to comparatively quick progress.

Regarding dummy effects per phase and site, Dutch chemical sites are shown to be quick in early development, and slow in implementation. Food firms are slow in development, while most chemical sites are quick to optimize (phase four). All firms except the food sites in the Netherlands take relatively long in the final implementation phase (phase five).

Table 4 Parameter Estimates for Industry Slices: '*chemical sites*' vs. '*food sites*'

slices	*chemical sites (c)*		*sd*	*food sites (f)*		*sd*
explanatory variables	$t(-1)$	-0.70	(0.09)	$t(-1)$	-0.33	(0.10)
	e_1	-0.40	(0.09)	$e_2(-1)$	0.59	(0.11)
	e_4	0.20	(0.07)	e_6	-0.26	(0.11)
	$e_5(-1)$	-0.30	(0.08)	e_7	0.54	(0.10)
	e_7	0.15	(0.07)	e_8	-0.75	(0.14)
	s_1	-0.35	(0.12)	s_4	-0.56	(0.14)
	s_2	0.34	(0.09)	s_7	-0.47	(0.13)
	s_8	0.59	(0.11)	s_8	0.31	(0.16)
dummy variables for phases and sites	d_2	-0.26	(0.14)	d_2	1.07	(0.17)
	(A-US)*d_2	0.65	(0.26)	(H-NL)*d_3	0.63	(0.30)
	(D-US)*d_2	1.25	(0.28)	d_3	-0.49	(0.21)
	d_3	0.33	(0.12)	(U-NL)*d_4	-1.18	(0.30)
	(A-NL)*d_3	0.61	(0.26)	d_4	0.29	(0.16)
	d_4	-0.18	(0.14)	(US-f)*d_5	0.56	(0.31)
	(NL-c)*d_5	0.73	(0.23)	d_5	0.03	(0.20)
	d_5	0.61	(0.17)			
outliers	$(A\text{-}NL\text{-}3)_3$	-2.14	(0.44)			
	$(D\text{-}US\text{-}2)_5$	-1.29	(0.41)			
statistics:	No. of observations	56		No. of observations	44	
	R-squared	0.81		R-squared	0.75	
	Adjusted R-squared	0.73		Adjusted R-squared	0.63	
	Sum squared resids	4.81		Sum squared resids	4.92	
	Durbin-Watson stat	2.62		Durbin-Watson stat	1.82	
	Bera-Jarque stat	0.03		Bera-Jarque stat	0.49	

Results across Countries of Operation

The next pair of slices concerns common effects per country of operation. *For the sites in the Netherlands* specification efforts and planning clearly slow progress down (e_2 and e_3). In this respect, rigid and detailed planning are particularly unfavourable (s_5 and s_6). The sites appear to be struggling to keep information up-to-date *without* widening the scope of projects. Flexibility and focus appear difficult to combine. In particular, upward referral has a *negative* effect on project scope, and therefore on project progress. Specification efforts are pursued too long, especially on alternatives that are proven to be less attractive.

In contrast, *at sites in the US*, teams tend to choose more easily. Sound project definition and information on the internal context are crucial. These efforts reduce the time spent. Efforts to increase the specification detail and upward referral increase the time spent (as they also do in the Netherlands). Time leeway and final target uncertainty slow progress down as well. Most strikingly, though, feedback effects of phase duration are *insignificant*. Apparently, effort allocation is better to begin with, or, it is simply changed less whilst ignoring misdirections of efforts. Probably both.

Table 5 Parameter Estimates for Country Slices: 'Netherlands' vs. 'United States'

slice:	Netherlands (*NL*)		*sd*	United States (*US*)		*sd*
explanatory variables	$t(-1)$	-0.39	(0.07)	$t\ (-1)$	-0.10	(0.08)
	$e_2(-1)$	0.43	(0.09)	e_1	-0.28	(0.06)
	$e_3 + e_3(-1)$	0.29	(0.08)	e_2	0.18	(0.06)
	e_4	-0.30	(0.07)	$e_6(-1)$	-0.34	(0.06)
	$e_6(-1)$	-0.34	(0.09)	$e_8(-1)$	0.24	(0.08)
	e_7	0.19	(0.06)	s_2	0.17	(0.08)
	$e_8(-1)$	0.35	(0.11)	s_8	0.18	(0.08)
	s_1	-0.34	(0.13)			
	s_5	0.31	(0.10)			
	s_6	0.41	(0.11)			
dummy variables for phases and sites	d_2	-0.38	(0.16)	d_2	0.42	(0.13)
	(U-NL)*d_2	0.67	(0.25)	(U-US)*d_2	0.83	(0.22)
	(H-NL)*d_2	1.66	(0.26)	d_3	0.54	(0.10)
	d_3	0.25	(0.13)	(U-US)*d_3	-1.26	(0.23)
	d_4	0.06	(0.17)	d_4	-0.95	(0.12)
	(U-NL)*d_4	-0.63	(0.30)	(U-US)*d_4	1.69	(0.22)
	(A-NL)*d_4	-1.45	(0.39)	(A-US)*d_4	0.79	(0.18)
	d_5	-0.08	(0.20)	d_5	0.58	(0.11)
	(NL-C)*d_5	0.57	(0.26)	(A-US)*d_5	-0.74	(0.19)
outliers	$(\text{A-NL-1})_4$	1.59	(0.51)	$(\text{D-US-2})_5$	-1.07	(0.28)
				$(\text{D-US-4})_3$	-0.90	(0.28)
statistics:	No. of observations	57		No. of observations	43	
	R-squared	0.81		R-squared	0.91	
	Adjusted R-squared	0.72		Adjusted R-squared	0.85	
	Sum squared resids	5.47		Sum squared resids	1.39	
	Durbin-Watson stat	1.77		Durbin-Watson stat	1.77	
	Bera-Jarque stat	0.56		Bera-Jarque stat	0.82	

Results across Countries of Origin

The models for the countries of origin are relatively small and stable. Across both slices, definition/framing reduces R&D-time, and final target uncertainty makes phase duration longer. *At the sites of the Dutch companies*, once more, specification takes time and scope reduction saves it. Keeping R&D narrow and clear pays off. The negative effect of competition scanning is new. Apparently, sites of Dutch origin are simply not very effective at scanning for competitive action (and *therefore* take extra time). *At the sites of the American firms*, updating expectations slows progress down. Time leeway and planning rigidity also increase the R&D time spent. Sites of American origin seem to dislike handling large amounts of information. They are -and want to be- very focused, losing focus and speed if uncertainty, time leeway, or the frequency of new information grows. Planning rigidity is a substantial obstacle to progress. Several specific sites jump out in particular phases, but this merely indicates that effects in other slicings are important.

Table 6   Parameter Estimates for Origin Slices: 'Dutch firms' vs. 'American firms'

slice:	*Dutch firms (fnl)*		*sd*	*American firms (fus)*		*sd*
explanatory	$t(-1)$	-0.39	(0.09)	$t(-1)$	-0.58	(0.10)
variables	e_1	-0.23	(0.09)	e_1	-0.42	(0.08)
	$e_2+e_2(-1)$	0.27	(0.07)	e_7	0.39	(0.08)
	$e_4(-1)$	-0.20	(0.08)	s_2	0.50	(0.13)
	e_5	0.44	(0.11)	s_6	0.25	(0.12)
	s_8	0.47	(0.12)	s_8	0.81	(0.14)
dummy variables	d_2	-0.32	(0.18)	d_2	1.44	(0.18)
for phases and sites	(U-NL)*d_2	0.65	(0.26)	(D-NL)*d_2	-1.59	(0.26)
	(U-US)*d_2	1.43	(0.32)	$d3$	-0.10	(0.18)
	d_3	0.07	(0.14)	(D-NL)*d_3	0.73	(0.26)
	d_4	-0.12	(0.15)	(H-NL)*d_3	1.48	(0.36)
	(U-US)*d_4	0.98	(0.34)	d_4	-0.02	(0.15)
	d_5	0.68	(0.16)	(D-US)*d_4	-0.79	(0.23)
	(U-NL)*d_5	-0.92	(0.35)	d_5	0.34	(0.15)
				(D-NL)*d_5	1.64	(0.33)
outliers	(A-NL-2)$_5$	1.39	(0.44)	(H-NL-2)$_3$	-2.45	(0.47)
				(H-NL-2)$_5$	1.31	(0.43)
statistics:	No. of observations	47		No. of observations	53	
	R-squared	0.76		R-squared	0.81	
	Adjusted R-squared	0.65		Adjusted R-squared	0.73	
	Sum squared resids	4.67		Sum squared resids	4.95	
	Durbin-Watson stat	2.02		Durbin-Watson stat	1.96	
	Bera-Jarque stat	0.84		Bera-Jarque stat	0..09	

Results across Corporate Positions

Finally, we separate sites that are *at home* and *abroad*. Few effects in the slices below are really new. Most were encountered in one way or another in the previous slices. However, some new effects need to be evaluated. *At home*, more planning increases phase duration. Competitive scanning and upward referral slow progress down. Clarity about the internal context and about the range of opportunities improves progress (e_6 and s_9). *Abroad*, two results are puzzling. Firstly, efforts into definition/framing result in *longer* phase duration. The effect is very unlikely to be correct, since further investigation shows that this finding is very unstable across pairs of sites. The contrasting effect of competition scanning is also remarkable, but it fits economic theory very well. Information on competitive activities may be crucial to sites abroad, but it may just create confusion for sites at home, fitting economic theory on strategies for leaders and followers.

Table 7 Estimates for Corporate Position Slices: 'at home' vs. 'abroad'

slice:	*at home (mo)*		*sd*	*abroad (do)*		*sd*
explanatory variables	$t(-1)$	-0.24	(0.10)	$t(-1)$	-0.18	(0.08)
	$e_3(-1)$	0.56	(0.13)	$e_1(-1)$	0.34	(0.08)
	e_5	0.26	(0.12)	$e_2(-1)$	0.35	(0.09)
	$e_6+e_6(-1)$	-0.21	(0.08)	$e_4(-1)$	-0.23	(0.07)
	$e_8(-1)$	0.37	(0.12)	e_5	-0.47	(0.11)
	s_9	0.54	(0.10)	$e_6(-1)$	-0.28	(0.08)
				e_7	0.17	(0.07)
				$e_8(-1)$	0.35	(0.12)
				s_1	-0.65	(0.15)
				s_2	0.33	(0.12)
				s_3	0.22	(0.08)
				s_6	0.50	(0.10)
				s_7	-0.32	(0.12)
dummy variables for phases and sites	d_2	0.23	(0.16)	d_2	0.41	(0.17)
	(A-NL)*d_2	-1.20	(0.34)	(H-NL+A-US)*d_2	0.80	(0.22)
	d_3	-0.18	(0.21)	d_3	0.42	(0.13)
	(mo-c)*d_3	0.83	(0.30)	(U-US)*d_3	-1.04	(0.32)
	d_4	-0.16	(0.15)	d_4	0.33	(0.13)
	d_5	0.31	(0.22)	d_5	0.68	(0.15)
				(D-NL)*d_5	0.76	(0.29)
outliers	$(\text{D-US-2})_5$	-1.79	(0.51)			
	$(\text{H-US-2})_5$	1.24	(0.56)			
statistics:	No. of observations	50		No. of observations	50	
	R-squared	0.68		R-squared	0.83	
	Adjusted R-squared	0.56		Adjusted R-squared	0.72	
	Sum squared resids	7.72		Sum squared resids	3.58	
	Durbin-Watson stat	2.34		Durbin-Watson stat	2.21	
	Bera-Jarque stat	0.76		Bera-Jarque stat	1.00	

mo-c = chemical sites at home
mo = sites at home

6. Interpretation and Conclusions

Analysis of the slice models presented in this paper produces tailored advice to individual project- and site-managers on ways to improve their R&D performance. Often, the basic assumption in R&D theory is that more information is better, which is based on the premise that generic uncertainty is *the* critical obstacle to efficiency. In this line of reasoning, uncertainty blocks potential levels of success, and R&D would primarily be aimed at reducing uncertainties through gathering and processing information efficiently.

We find that *in practice* uncertainty reduction is pursued far less than *in principle* would be possible. Even given constraints on budget and time, the reduction of uncertainty is limited to what is only strictly necessary. This typifies *effective* R&D. *Only a fraction of possible information is used*, applying efficient short cuts. To success, the *effective* use of information seems crucial. This means limiting attention to only a fraction of the available information. Obviously, the art lies in the fact that it cannot be known a priori which information will be crucial.

The analysis above has shown that effective R&D in terms of shorter time to implementation requires clarity of goals and flexibility in progress. The central finding is that the information in use ought to be minimized wherever feasible. Information overload is a serious threat to effectiveness of innovation development efforts. Therefore, across contexts, it is critical to narrow down the complexity of the information set in use. Continuous attempts to minimize the information processing requirements are in order, to make effective decisions in the end.

The downside of limited information is obviously an increased probability of making mistakes. There is a limit on the desirable minimization of information use. Additionally, effective error signaling and correcting mechanisms are desirable to make sure losses are bounded. If information contradicts the working model, it should only bother those doing the R&D until some threshold is passed. There will always be a trade-off between a narrow working model and frequent scope changes. The broader the model, the fewer scope changes occur. At the same time, such a broader model means that more adjustments in efforts take place during each phase. Short-term error correction takes place *within* the effort-allocation-process.

The scope of the relevant alternatives and contexts per typical project is found to differ between the slices in our data set. Projects seem to be kept particularly broad in scope at the chemical firms, especially in the Netherlands. Between food firms, the projects in the Netherlands are also broader in scope than in the United States. Related to this, the projects in chemcials and in the Netherlands seem to be more in need of short-term correction. The latter is one of the major findings of our comparison of effort-allocation in R&D: *short-term corrections are systematically required less in the US*. Effort-allocation and its impact on time spent per phase are more stable at sites in the US. There are fewer adjustments, both within and across phases.

Chemical sites are relatively quick in early development, but relatively slow in final implementation. It seems that definition/framing efforts are generally reduced too early, and competition scanning efforts pursued too late. As a result, hard choices are still needed in the final phases, leading to repeated scope changes, late in R&D progress.

At the food sites, it seems particularly crucial to keep the scope of R&D efforts narrow. The effects of specification and updating expectations are particularly strong, so strong project support is desirable for effective R&D. This seems to indicate that R&D in the food sector should be aimed at only a few strongly prioritized projects.

A number of other context-specific features has been identified. R&D projects in the US are slower under uncertainty. The desire to exercise control over uncertainty seems to dictate step-wise R&D: branched, separated, and specialized. Of course, this is not to say that radical innovation does not arise in American R&D. Clarity of goals just seems to be very desirable, especially if innovations are complex and uncertain. Uncertain targets and horizons hardly impact R&D progress in the Netherlands. Apparently, in the Netherlands clarity of goals is not as crucial as in the US.

A final context-specific result holds in general for sites abroad. It seems that competition scanning can structurally improve the speed of innovation. *Flexible innovation* is the catchword for subsidiaries abroad, which means that projects with a narrow focus are much more able to swiftly react to market changes. Alert behaviour is very crucial abroad, since market power is more difficult to secure at foreign sites.

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Appendix

1. Repeated Estimation

The idea behind repeated estimation of slices is that we approach the meta-model:

(2)

Again, $\underline{t}$ and $\underline{t}_{-1}$ are NJ $\times$ 1 vectors of observations on phase duration and lagged phase duration, respectively. The is the NJ $\times$ 1 vector of dummy variables, and, again, the assumptions on the errors are $N(\underline{0}, s^{2}{}_{\chi} I_{NM})$. is a NJ $\times$ NJ matrix with parameters $b_{0,i,j}$ (specific per phase and per site). The parameters are blocked on the diagonal in $n_i \times 1$ row vectors. The n_i is the number of projects at site i (i =1 to 8, for *A-NL* to *H-US*)). Next, X is a NJ $\times$ KNJ block-diagonal matrix with blocks $X_{i,j}$ on the diagonal. The $X_{i,j}$ are $i \times$ K blocks of the observations on e_k, $e_{k,-1}$, and s_l at site i. They are the same as the corresponding block of the X-matrix in equation 6.3.1. is a KNJ $\times$ 1 vector of effort-, lagged effort- and project feature parameters that are now specific per phase and per site. These parameters are simply the stacked generalization of the $\underline{\beta}$-vector in equation 6.3.1. The only difference with equation 6.3.1 is that we allow site- and phase-dependence of all the parameters in equation 6.3.2. It seems desirable to present the , and X in some more detail:

Box 1 Matrices of Parameters (B_0 and $\underline{B}$) and Explanatory Variables (X)

The iterative procedures of estimation and reduction are now applied in the determination of relationships between $\underline{t}$, $\underline{e}_k$, and $\underline{s}_l$ per *slice of sites* (see Table 1). First, estimated relationships are derived for each industry. They simply describe the relationship between $\underline{t}$, $\underline{e}_k$, and $\underline{s}_l$ based on half the data set.

Equations 3 and 4 show the two basic slice models.

(3) c for 'chemicals'

and

(4) f for 'food'

Second, we estimate and reduce equations *per country of operation*. These results that are now derived allow different relationships for the sites in the Netherlands and for the sites in the United States. We study, one at a time:

(5) NL for 'Netherlands'

and

(6) US for 'United States'

Third, we allow parameters to vary across *countries of origin*. This discriminates *Dutch* and *American* firms. The slices are labelled *fnl* and *fus*, and they include respectively the sites *A-NL*, *U-NL*, *A-US*, and *U-US*, and the sites *D-US*, *H-US*, *D-NL* and *H-NL*. The equations are estimated and reduced analogously to before.

Fourth, we vary parameters across the *corporate position* of the sites. This discriminates between *at home* and *abroad*, delineating the slices {*A-NL*, *U-NL*, *D-US*, *H-US*} and {*D-NL*, *H-NL*, *A-US*, *U-US*}. Again, we derive estimates of equations analogous to 5 and 6.

Finally, following assumption V, we split the data set into *phases 2 and 3*, and, *phases 4 and 5*. As it turns out, these *time*-slices show particularly many of the causalities encountered in the other slices. *Therefore, we choose to describe the relationships based on assumption V, before continuing on the other four slicings I-IV*. This will allow us to explain results in the other slices relative to these *time*-slices.

2. Estimation Routine

We estimate and reduce the models by way of the following procedures. In the estimation and reduction of the slice models that follow, the same routine is applied.

- We start with the largest model, incorporating all effort-, lagged effort- and project feature variables in the *X*-matrix, and a full vector of dummy variables $\underline{d}$;
- Iteratively, then, we reduce the model by omitting, one by one, the explanatory variable that is 'most

- The reduction process is continued up to the moment that only variables remain that cannot be omitted without seriously deteriorating the explanatory power of the model (i.e. the sum of squared residuals does not increase dramatically);
- In the meantime, after each omission, the errors are checked to be $N(\underline{0}, s^2 \times I_{NM})$. Sometimes a dummy variable is included to handle outlying project phases. Of course, it is checked whether these outliers make sense qualitatively;
- After each omission, the loss of explanatory power is also checked. This is done in order to avoid 'accidentally' dropping crucial variables;
- When the described reduction process has come to a stop, the vector of dummies $\underline{d}$ is investigated. Parameters are tested for equality across sites (one pair at a time). If differences are insignificant (1%), the dummy variables are restricted to be equal;
- After this recombination of the dummy variables, the remaining 'normal' variables are tested again. If any have become insignificant, they are referred to the error structure, *unless* the explanatory power drops dramatically;

Although it cannot be guaranteed that this is indeed the best estimate of the relationship, it is typically a very good and reliable one[8]. Subsequently, the reduced model is tested on parameter constancy across pairs of sites.

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[8] Monte Carlo-simulations have been executed to test size and power of the procedures. These results were very reassuring. Similar reduction procedures are commonly applied in empirical econometrics.