

Measuring the Effectiveness of Overlapping Development Activities

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Overlapping development activities is widely used to reduce project completion times in product development. However, research on the applicability of the concept in different technological environments remains scarce. So far, very few industry-specific studies have statistically confirmed an accelerating effect of overlap. In the present article we statistically measure the effectiveness of overlapping development activities in reducing project completion time. Building on analytical research in operations management, we argue that this effectiveness differs with the organization's capability to resolve uncertainty early in the process. Projects benefit more from overlap if they are able to resolve uncertainty early. This contingency view to overlapping development activities is tested based on data from 140 completed development projects across several global electronics industries.

(Product Development; Concurrent Engineering; Simultaneous Engineering; Activity Overlapping; Time-to-Market; Electronics Industry; Regression)

1. Introduction

Time-to-market in product development has been viewed as an important factor for success in the 1990s (e.g., Blackburn 1991, Wheelwright and Clark 1992). Landmark studies by Takeuchi and Nonaka (1986) and Clark and Fujimoto (1991) demonstrated that overlapping of activities is a powerful tool for reducing product development times in the automobile industry. Overlapping has also been used successfully in developing airplanes (Sabbagh 1996) and software (Cusumano and Selby 1995). Today, overlapping activities and the surrounding organizational activities needed to support it are widely used and often referred to as simultaneous engineering (Griffin 1996).

Despite many success stories, there is recent evidence that overlapping activities can come at the expense of development rework, especially if development uncertainty is not resolved early during a

project. Such rework may outweigh the overlap benefits of parallel task execution. First, based on managerial experience, several authors recommend restricting the practice of overlapping to environments of low uncertainty (e.g., Cordero 1991, Lincke 1995). Second, there is a growing body of literature in operations management that has modeled the question of when one should overlap development activities and has, at least partially, drawn similar conclusions (Krishnan et al. 1997, Ha and Porteus 1995, Loch and Terwiesch 1998).

The contribution of the present article is twofold. First, we confirm the acceleration impact of overlap on project completion time. This relationship has only been statistically confirmed in very few industry-specific studies. Second, building on the above-mentioned operations management literature, we provide a model that hypothesizes the optimal overlap

level to depend on the *uncertainty resolution* in the project. We operationalize the concept of uncertainty resolution and statistically show how it influences the effectiveness of overlap using data from 140 completed development projects across several global electronics industries.

The article is organized as follows. Section 2 reviews the relevant literature on activity overlap in development. In §3, we develop the hypotheses. After a description of our methodology (§4) we test the hypotheses in §5. The article ends with a discussion of our results and a preview of future research.

2. Literature Background

Overlapping development activities has been recognized as a key component of concurrent engineering for reducing development times over the last decade. Imai et al. (1985) and Takeuchi and Nonaka (1986) report that faster development processes can be achieved by overlapping activities. Similar observations were reported by Sabbagh (1996) in the development of the Boeing 777, and by Cusumano and Selby (1995), as well as Blackburn et al. (1996) for software development.

In their famous study of product development practices in the world automobile industry, Clark and Fujimoto (1991) showed that overlapping activities accelerated the product development process. With their construct "Engineering Simultaneity Ratio," they were the first to operationalize overlapping development activities and to identify a statistically significant accelerating effect on engineering lead times. In addition, Clark and Fujimoto examined the organizational context, in which overlapping activities is beneficial. Using an information processing framework (Galbraith 1973, Tushman and Nadler 1978), they identified intensive communication as a key success factor. These ideas were refined in further studies, including those by Wheelwright and Clark (1992) and Clark and Wheelwright (1994).

In their study of the world computer industries, Eisenhardt and Tabrizi (1995) identify substantial differences in development strategies across industries. For the stable and mature mainframe and microcomputer industries, the authors find that a compression

strategy significantly reduces time-to-market. The compression strategy is based on overlapping activities, shortening activities, and rewarding developers for attaining the compressed schedule. However, in rapidly changing markets such as printers and personal computers ("high velocity environments" in the words of Eisenhardt 1989), the compression strategy (and thus overlap) does not provide a significant acceleration. The highest performing strategy under such conditions is an experiential strategy, which means using frequent iterations and short times between milestones. Eisenhardt and Tabrizi argue that compressing the development process through activity overlaps only yields a time reduction if the market environment is stable and predictable. Reports based on managerial experience also caution that overlapping should be used mainly for "moderate levels of innovation" (Cordero 1991).

Recently, a number of analytical models have been developed uncovering trade-offs involved in overlapping activities. Krishnan et al. (1997) develop an illustrative framework of two development activities, an information supplying upstream activity and an information absorbing downstream activity. The framework introduces the concepts of upstream evolution and downstream sensitivity. Upstream evolution is defined as the reliability of preliminary information released by the upstream activity. If one takes the creation of a design parameter (e.g., an axle diameter) as an example for the upstream output, one can plot the set of possible outcomes as a sequence of intervals. Initially, the interval for the parameter is wide, then narrows over time and converges to the outcome parameter. The speed of this convergence is called the evolution function. Thus, fast evolution represents an early resolution of uncertainty. Downstream sensitivity is a measure of dependence and describes how much downstream rework is caused by modifications coming from upstream.

Loch and Terwiesch (1998) conceptualize uncertainty in the form of engineering changes: The more uncertain the upstream activity, the more engineering changes (ECs) will occur during the project. ECs have the universal characteristic that they become more difficult to implement the later they occur. Loch and

Terwiesch formalize the problem of finding the level of activity overlap that minimizes expected project duration, where engineering changes are generated stochastically. By performing sensitivity analysis on the optimal level of activity overlap, they find that overlap gains increase with fewer and earlier engineering changes. They also show the impact of different communication patterns on the overlap problem.

Ha and Porteus (1995) model the situation of two interdependent activities, product design and process design. In this situation, overlap is the “natural” way to proceed because otherwise severe quality problems result. Quality gains have to be traded off with time penalties for cross functional meetings. The key question is how often to meet and update (“how far to let one activity run ahead”). The model shows that a weakening of the reciprocal dependence (i.e., the quality problems) makes the situation more similar to an upstream-downstream problem as in the models above, calling for less overlap. In addition, the authors recommend less overlap in the presence of high communication costs.

The present article uses the emerging operations management literature on activity overlapping to develop a refined model of the relationship between overlap and project completion time. It thus extends the earlier work on overlap by Takeuchi and Nonaka (1986) and Clark and Fujimoto (1991). The model is built around the new concept of uncertainty resolution. We operationalize uncertainty resolution by providing a first measure and show how it significantly influences the effectiveness of overlap. With the concept of uncertainty resolution, we provide a more detailed description of project uncertainty than Eisenhardt and Tabrizi (1995), who view uncertainty as largely driven by the market environment. Having a measure of uncertainty resolution allows us to use a wider range of industries in our sample (13 segments of the electronics industries compared to 4 in Eisenhardt and Tabrizi), and thus to use a different econometric methodology.

3. Development of Hypotheses

The acceleration impact of overlap on project completion time has been reported in countless articles. The

underlying reasoning for this acceleration effect is simple. Instead of organizing a development project in a purely sequential manner performing one task after the other (Takeuchi and Nonaka call this “relay race”), the team should concurrently work on several tasks. This facilitates communication between the tasks and also yields an overall compressed development process.

Despite the popularity of the concept, few studies have managed to measure an acceleration effect of overlap. Clark and Fujimoto (1991) find such an effect in their study of engineering problem solving in the automobile industry. They define the “simultaneity ratio” as the proportion of the development time that occurs in parallel to the die cutting process. Using regression analysis, they then show a significant time-reducing effect of the simultaneity ratio on engineering lead time (significant at the 5% level).

Using the same overlap measure, Eisenhardt and Tabrizi (1995) find similar results in the mainframe and workstation industry (significant at the 10% level). These statistical findings together with the widely quoted anecdotal evidence motivate our first hypothesis:

Hypothesis 1. Overlapping activities reduces project completion time.

However, a compression of the development process through overlapping requires a situation with limited uncertainty where changes are foreseeable and can be kept under control. Otherwise, overlapping may cause substantial rework, outweighing the time gain from overlapping. This is consistent with the operations management approaches to the problem reviewed above. The concept of the evolution function developed by Krishnan et al. operationalizes the resolution of uncertainty over time. That model hypothesizes larger overlap benefits for situations with fast evolution (uncertainty is reduced early) in contrast to those with slow evolution: “Overlapping activities is generally easier when the upstream evolution is fast rather than when it is slow” (Krishnan et al. 1997). The concept is illustrated for the case of a door handle, a pager, and for parts of a dashboard (Krishnan 1996).

In an analytical model, Loch and Terwiesch (1998) describe the concept of uncertainty resolution as the

distribution of engineering changes over the course of the project. The later an engineering change occurs, the more time it takes to adjust work by other activities that are done concurrently. For example, a geometric change in the design of a plastic component can be instantaneously implemented as long as the tooling process is working at a CAD level. Even with prototype tools, changes can be performed rapidly. However, once the molds are made from a material suitable for volume production, the same engineering change can create major delays (Terwiesch and Loch 1999, Gatenby 1994). Thus, the time gains resulting from overlapping activities are larger if uncertainty is reduced early in the process.

The idea of increasing the benefits of overlap by moving forward engineering changes has also been extensively discussed by practitioners under the name of "Frontloading." Frontloading refers to a number of methodologies including early reviews, rapid prototyping, and CAx technologies, that allow an earlier detection of potential engineering problems (Fujimoto 1996) and thus an earlier final specification of the product. Taking together this industrial practice and the operations management approaches, we state our second hypothesis as:

Hypothesis 2. In projects with fast uncertainty resolution, time gains from activity overlap are larger than in projects with slow uncertainty resolution.

Based on Hypothesis 2, it would be natural to expect that project managers minimize project completion time by optimizing overlap. Even if this optimization is not exact, one would expect that the overlap decision at least goes in "the right direction," that is, that less overlap is used when uncertainty resolution is slow.

This is consistent with the theoretical literature on overlap reviewed above (Krishnan et al. 1997, Loch and Terwiesch 1998). It also is in line with previous research on project management as well as reports from practitioners (Cordero 1991). For example, both Morris and Hough (1987) and Lincke (1995) recommend less overlap for high technology/high uncertainty projects. We therefore state Hypothesis 3 as:

Hypothesis 3. Projects with fast uncertainty resolu-

tion use more activity overlap than projects with slow uncertainty resolution.

From a methodological perspective, Hypothesis 2 suggests a moderation effect of uncertainty resolution: The impact of overlap on project duration increases with the ability of the project team to reduce the uncertainty early in the process. The corresponding statistical test for such a hypothesis consists of comparing regression coefficients across different values of the moderating variable (Arnold 1982, Venkatraman 1989). Thus, we use multiple regression analysis as our primary statistical tool. A support for Hypothesis 1 would require a significant effect in a model with project completion time as the dependent variable and overlap as an independent variable. Hypothesis 2 is supported, if the regression coefficients for the overlap variable differ across different levels of the uncertainty resolution variable. Finally, support for Hypothesis 3 requires uncertainty resolution to be a significant predictor of overlap.

4. Empirical Methodology

Our analysis is based on a sample of 102 electronics companies in the US, Japan, and Europe. During 1992–1993, these companies completed detailed questionnaires on operations and strategy for one business unit as part of the "Excellence in Electronics" project jointly undertaken by Stanford University, the University of Augsburg and McKinsey & Company. Parts of the sample have already been used for other research projects (e.g., Eisenhardt and Tabrizi 1995, Terwiesch et al. 1996). Many worldwide leading electronics companies agreed to participate in the survey, providing us with data on 12 of the 25 leading computer producers and four of the six biggest TV manufacturers. The unit of analysis of our work is the individual development project. Each participating business unit contributed two new product development projects.

4.1. Data Collection

Our analysis of product development in the electronics industry is only one part of a larger data collection effort. In addition to product development, the overall instrument contained questions on marketing, manufacturing, finance, and top management, which were

used in other research projects (e.g., Terwiesch et al. 1998). The product development part consisted of a group of general questions concerning product development practices of the business unit, and a subsection for each of two specific projects. These were used for the research presented in this article. To avoid biases coming from hindsight reasoning and retrospective sensemaking, we focused on technical questions with closed form answers.

We organized the 204 projects into 14 product groups such as TV, medical devices, PC, telephone, etc. This grouping allowed us to compare similar development projects with one another and to standardize certain measures within a product subsample (see below).

Some of the projects were small, peripheral modifications involving only one or two engineers. Since our research focus is on product development projects, we decided to omit 64 projects that had an effort of under five person years from our statistical analysis. Two other projects were excluded because their technical content was unique in the sample, prohibiting benchmarking with others. The remaining sample included 140 observations. The subgroup sizes are reported in Table A in the Appendix.

4.2. Measures

The duration of a development project is not only influenced by overlap. Previous research identified and confirmed the importance of several other predicting variables (e.g., Eisenhardt and Tabrizi 1995), namely the use of testing, time span between milestones, the number of design iterations, and the redesign frequency (to be defined below). We include these predictors in our regression analysis for two reasons. First, leaving out variables that influence the dependent variable (project duration) can potentially create biases. Second, in addition to the hypothesized moderating effect on overlap, uncertainty resolution could also have similar effects on these other variables. The additional effects of uncertainty resolution are thus interesting by-products of our statistical analysis.

Since our research focus is on development time, we used the *standardized project duration* as our dependent variable. Project duration was defined as the time from the first project meeting until the targeted pro-

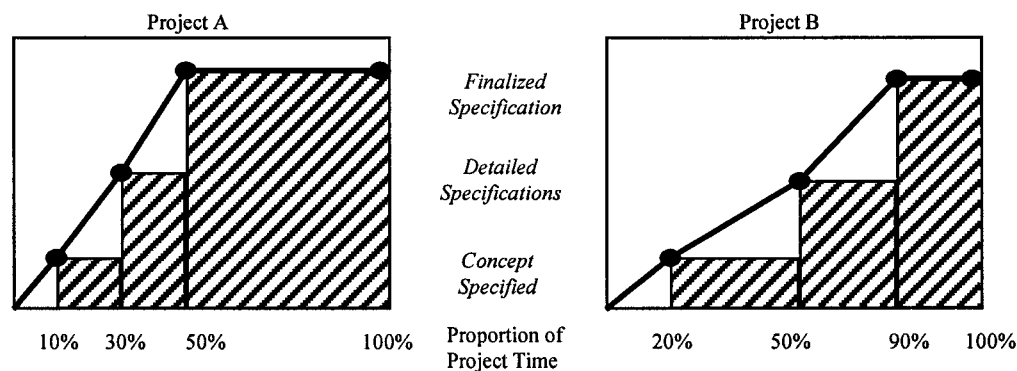
duction volume had been reached and the production process had been stabilized. The standardization was performed by taking the difference between the project duration and its industry subsample average, divided by the industry subsample average. That is, a project of average length in its product group was given the measure zero. Although projects within a subsample are homogeneous concerning the developed product, they can still differ in their technical content. In this article we are not interested in this *size effect*, but in the effect of different project management decisions. Since it is reasonable to assume that large projects take longer than small ones, we controlled for this size effect by including a control variable in the regressions. Size was measured by project effort (in person years) and standardized as previously described.

In the questionnaire, a development project was structured into six phases: predevelopment study (to completion of basic product requirements), conceptual design (to specification of all product functions), product design and engineering (to system testing release), system testing (to production release), final process development and scale-up (through completion of pilot production run), and production start-up (to stabilization).

We measured *overlap* as the sum of the overlaps between subsequent phases divided by the gross duration of the project without deducting overlap (i.e., the sum of the development phases). The higher this ratio, the more overlap was used in the project. This measurement of project concurrency follows the approach by Clark and Fujimoto (1991) and that of Eisenhardt and Tabrizi (1995). Similarly, we defined *testing* as the ratio of the testing phase duration and the sum of the other phase durations.

Time between milestones was measured by the average number of weeks between two officially scheduled project reviews. Only milestones with a detailed project review were included. We measured the number of design *iterations* by asking how many redesign iterations the product took before stabilization (as defined above: stable volume production). A redesign iteration was defined as a modification of more than 10% of product components. Prototyping is a typical

Figure 1 Measure of Uncertainty Resolution: Uncertainty Resolution is Fast in the Left Project (Project A) and Slow in the Right Project (Project B)



example of such a type of iteration, whereas debugging does not classify as an iteration. As products in the electronics industry are significantly influenced by their software, we used as our measure the larger of the number of hardware iterations and software iterations. For example, if a project had five hardware iterations and seven software iterations, we used seven for our measure. We measure *redesign frequency* by looking at the length of the time interval between two product generations (in months). We then include the length of the interval—mathematically the reciprocal of the redesign frequency—in our regression model. Frequent redesigns should yield a faster development process as the business unit has more recent experience in undertaking similar development projects and the level of technical obsolescence of the current product is lower. As the magnitude of these items might substantially differ across product sub-samples, all three were standardized in the same way as project duration.

While the previous measures could be derived directly from the questionnaire, our measure of uncertainty resolution had to be constructed by combining different items. An operationalization of the residual uncertainty over the project duration is not straightforward. As a proxy, we used the three milestones “preliminary information release,” “detailed specifications defined,” and “specifications frozen.” These are well-known industry terms, which we link with relative phase durations to create an uncertainty curve.

As an illustration, consider two projects. Project A (left in Figure 1), reaches the level of preliminary

information release after 10% of project time, detailed specifications were defined after 30%, and the final specifications were reached after 50%. Project B first releases information after 20%, detailed specifications after 50%, and freezes the design after 90% of the total project time. These data provide an uncertainty resolution curve. As a measure of uncertainty resolution, we used the area of the shaded rectangles in Figure 1. Uncertainty resolution is faster for Project A which has the larger shaded rectangle area. Descriptive statistics and correlations among all variables are also given in the Appendix.

5. Regression Results

Model 1 shows the control effect of project size on the dependent variable. As expected, the control variable is significant, but only 24% of the variance in project

Table 1 Results of Regression Analysis for Development Time

Variable	Model 1	Model 2
Project Size	0.155***	0.130***
Overlap		−0.591***
Testing		−0.593*
Time Between Milestones		0.152***
Iterations		0.146***
1/Redesign Frequency		0.127**
Uncertainty Resolution		−0.044
Adj R ²	0.24***	0.445***

* <0.10; ** <0.05; *** <0.01; N = 140.

duration can be explained by size. The second regression model adds the variables that we expected would influence project duration. The estimated coefficients, model fit, and significance are also reported in Table 1.

Looking at the beta coefficient of overlap (-0.59) and its significance level (1%) we find a significant overlap benefit across levels of the contextual variable “uncertainty resolution.” More overlap yields shorter project duration with high statistical significance. We thus find strong support for the main effect as outlined in Hypothesis 1. The overall fit of Model 2 is surprisingly high: 45% of the variance is explained by our model, of which only 24% can be attributed to the control variable. This compares to 36% in the Clark and Fujimoto study (where simultaneity ratio is significant at 5% level) and 35% to 47% in the Eisenhardt and Tabrizi study (the authors have multiple regression models with overlap being significant at the 10% level).

A high proportion of project time dedicated to testing reduces completion time, but is not of high statistical significance. Frequent milestones (that is, short times between milestones) significantly reduce project duration. If the project needs many iterations to reach its final product design, the project is delayed. A low redesign frequency creates a higher technical content of the project and therefore—as expected—delays project completion.

We now turn to the hypothesized impact of uncertainty resolution on project duration. Table 1 indicates at first sight that uncertainty resolution does not influence project duration. However, the absence of significance only describes the direct effect of uncertainty resolution. Our hypothesis is about its indirect (moderating) effect.

6. Moderating Effect of Uncertainty Resolution

To explore the moderation effect of uncertainty resolution, we performed a subgroup analysis. As we hypothesized uncertainty resolution to be the contextual variable, we divided our sample into two halves, below and above the median uncertainty resolution score. Support of our hypothesis would require sig-

Table 2 Split Sample Analysis with Uncertainty Resolution

Variable	Model 3 ^a	Model 4 ^b
Project Size	0.155***	0.118***
Overlap	-0.913^{***}	-0.339
Testing	0.041	-1.699^{***}
Time Between Milestones	0.178***	0.111*
Iterations	0.196***	0.138***
1/Redesign Frequency	0.106	0.102
Adj R ²	0.48***	0.47***

* <0.10 ; ** <0.05 ; *** <0.01 .

^a $N = 70$: fast uncertainty resolution.

^b $N = 70$: slow uncertainty resolution.

nificant differences across the two subsamples. The results are reported in Table 2.

Model 3 describes the subsample with fast uncertainty resolution. Overlap is significant at the 1% level, indicating that early uncertainty resolution makes overlap more successful. It is also noteworthy that the beta coefficient describing the acceleration effect of concurrency is, in absolute terms, substantially higher than in Model 2. Model 4 includes the observations that have a slower uncertainty resolution than the median. The significant influence of overlap (at the 1% level in Model 3) disappears.

The significant influence of testing observed in Model 4 is in contrast to Model 3 (where testing has a positive sign). That is, testing in projects with fast uncertainty resolution seems to have a delaying, rather than an accelerating, effect. In a project with slow uncertainty resolution in contrast, testing contributes significantly to short development times. Its beta coefficient is, in absolute terms, far higher than in the overall regression and highly significant (0.1% in Model 4).

In addition to testing and overlap, other variables also change significance: The practice of frequent milestones seems less applicable in the case of late uncertainty resolution. If the path of the project cannot be predicted initially, milestones are difficult to define and are thus a less effective way of time reduction. However, if the project is highly predictable, milestones provide a useful tool for project management in keeping diverse activities coordinated and maintaining control of the total project. This result is

remarkable, as Eisenhardt and Tabrizi make “time between milestones” part of their experiential strategy. Our observation that the effect of frequent milestones on project duration is moderated by uncertainty resolution provides an interesting alternative explanation. Iteration has a delaying impact in both subsamples and remains unchanged from Model 2. The variable redesign frequency loses its significance, compared to Table 1. As the signs of the corresponding beta coefficients remain unchanged, we can attribute this loss of significance to the reduced sample sizes (now 70 instead of 140).

The different beta coefficients and significance levels reported in Table 2 suggest that uncertainty resolution has a moderating effect on project duration rather than a direct one. However, to formally support our hypothesis, we need to test for a statistical difference between the beta coefficients of Models 3 and 4 (see our discussion under Hypothesis 3). This can be done using a simple *t*-test, which compares the value of the beta coefficients ($-.913$ vs. $-.339$) relative to the estimated standard errors. The test is significant at the 5% level.

In order to test whether the way we divided the sample into subsamples was robust to perturbations, we used splits based on other subsample sizes (80:60, 60:80) in addition to the median split (70:70). Repeating the statistical analysis as presented in Table 2 on these modified subsamples, we found that the structure of our results remained unchanged.

A more formal way of testing for the equality of coefficients of different regressions is given by the Chow-test (Chow 1960). To test whether the assumption of two separate regression models is correct, one starts with the null hypothesis that the regressions are identical and sees whether or not this hypothesis can be rejected. The test is based on a comparison of the sum of squares for the two separate models (Models 3 and 4) and the sum of squares from the overall model (Model 2). In econometric terminology the model using two separate regressions is called *unrestricted* and the overall regression is called *restricted*. The Chow-test is an *F*-test where the degrees of freedom are given by the sample sizes (70 each in our case) and the number of

restrictions on the beta coefficients. For our specific case, the test rejects the null hypothesis (at 5% significance); thus the beta coefficients do change across subsamples.

To test Hypothesis 3, we divided our sample into two subgroups, below and above the median value of the uncertainty resolution measure. Support of the hypothesis would require a significant difference in overlap across these two subsamples. However, comparing the mean overlaps across the two subgroups did not show any significant difference. Moreover, a regression analysis with overlap as the dependent and uncertainty resolution as an independent variable does not explain any variance. Thus, Hypothesis 3 is not supported by our data.

Project managers in our sample did not choose the overlap level according to uncertainty resolution. We admit that the recommendation to choose overlap in line with uncertainty resolution is easily made *ex-post*. In other words, it is easy for the researcher to recommend what *would have been* an appropriate level of overlap. However, the project manager needs to choose the overlap level *during* the evolving project. At this point, computing the uncertainty resolution measure as described in Figure 1 is very difficult. Future research will have to provide concepts and tools that allow a project manager to estimate uncertainty resolution earlier on, during the project. Whereas the product development literature has not yet addressed this question, software engineering has generated a number of tools that could support such an estimation (see Putman and Myers 1992).

7. Discussion

Our hypotheses address two gaps in the existing literature on activity overlapping. First, research on concurrent engineering has not sufficiently addressed the influence of contextual variables on the effectiveness of overlapping development activities. Second, there is a lot of anecdotal evidence on the benefits of overlapping, but only a few industry-specific studies could find a significant acceleration effect of overlap.

Based on an emerging research stream in Operations Management we hypothesized overlap to reduce

project duration. We further claimed that these overlap benefits would differ according to a third (moderating) variable; uncertainty resolution; and that we would therefore expect to find more overlap in projects with fast uncertainty resolution.

The hypotheses are tested on data drawn from 140 completed development projects across global electronics industries. We first test the influence of overlap on project completion time across the full range of our sample. We find overlap to be a significant accelerator of development time. This finding is important as it generalizes the two previous studies to a wider range of industries. We then compare the size of this acceleration effect across different levels of our uncertainty resolution measure. We find the acceleration effect only to be significant if uncertainty resolution is fast. To our surprise, faster uncertainty resolution was not combined with more overlap. This finding is of substantial managerial interest, as it suggests that projects in our sample could have reduced their project duration by choosing the overlap level according to Hypothesis 2. Our study is based on data from a relatively large, heterogeneous sample. Highly significant results and, at the same time, a relatively good measure of fit increase the generalizability of our research findings.

If the uncertainty resolution over the course of the project is unfavorable for overlapping activities and cannot be sufficiently accelerated by defining standards and architectures, the project organization has to search for other means of uncertainty resolution. The use of prototypes is a well-known project management decision in such a contingency (e.g., Wheelwright and Clark 1992). Instead of following an overlapped phase process, design-build-test loops are used as a learning facility. In that case, a project then experiences a highly nonlinear and iterative process which relies on experiencing product performance based on testing. The regression reported above suggests testing as an alternative way of reducing development time for projects where fast uncertainty resolution cannot be achieved. The corresponding beta coefficient changes in the opposite direction to the one of overlap. Such an approach is consistent with the Eisenhardt and Tabrizi concept of “experiential strat-

egy” that relies on frequent iterations and the rapid building of experience.

In our analysis, we have treated uncertainty resolution as an exogenous variable, thus outside the scope of our model. As can be seen in Table B, this approach is correct from a purely statistical perspective: None of the other variables shows a significant correlation to uncertainty resolution. In an industrial context however, a project manager has more decision variables than overlap alone. For example, Thomke (1997) shows how simulation and experimentation can help to eliminate uncertainty early in the development process. What exactly drives uncertainty resolution, how it can be estimated, and how it can be changed by managerial action seems to be an interesting subject for future research.

8. Conclusion and Future Research

This article links two, up to now distinct, streams of research on concurrent engineering. The emerging construct of uncertainty resolution is found to significantly moderate the impact of overlap on project duration (e.g. Eisenhardt and Tabrizi 1995). This confirms theoretical work in operations management (Krishnan et al. 1997, Loch and Terwiesch 1998) that indeed there are trade-offs in choosing the appropriate overlap level.

This view of concurrent engineering creates several opportunities for future research. First, new measures of uncertainty resolution will have to be developed. New measures should explicitly consider the specific needs of project managers, who have to know the uncertainty resolution *ex-ante* rather than *ex-post*. Second, we did not address the question of where uncertainty resolution originates. Both rapidly changing markets and uncertainty inherent in the technology may force project teams to freeze their specifications late. On the other hand, uncertainty resolution may be an organizational capability that can be learned over the course of several projects. Thus, demonstrating the importance of a fast uncertainty resolution is only the first step. A next research step must provide better insights into the *process* of this uncertainty resolution. With the growing impact of information technologies on the product development process, the way

Table A Number of Observations per Industry

Industry	Number of Observations
Mainframes	8
Large Medical Systems	6
Small Medical Systems	8
Industrial Controls	17
Test and Measurement Systems	16
PCs	24
PBXs	5
Printers	16
Minicomputers	12
Data Communication Systems	4
TV/VCR	17
Telephone Endsets	4
Computer Peripheral	3

Table B Means, Standard Deviations, and Zero-order Correlations

Variable	Mean	S.D.	1	2	3	4	5	6	7
1. Project Duration	0	0.42							
2. Project Size	0	1.37	0.50						
3. Overlap	0.25	0.13	-0.24	-0.01					
4. Testing	0.17	0.08	-0.20	-0.03	0.29				
5. Time Between M.	0	0.66	0.41	0.16	-0.20	-0.13			
6. Iterations	0	0.67	0.26	0.09	0.11	0.04	0.01		
7. 1/Redesign Freq.	0	0.50	0.30	0.14	-0.01	-0.01	0.29	0.08	
8. Uncertainty Res.	0.50	0.50	-0.01	0.13	0.09	-0.07	-0.05	-0.01	0.06

companies resolve project uncertainty is drastically changing and provides a third opportunity for further research.

Appendix

The following two tables provide information on the sample composition and basic descriptive statistics.

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