Ramp-up Performance in Consumer Electronics

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To a scientist, delight is not found in recognition

but in the joyful moment of insight

*Hans-Jürgen Quadbeck-Seeger (*1939)*
German chemist

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Andreas Pufall

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Chapter 1

Introduction

New product development (NPD) is particularly challenging in the high-technology sector that is increasingly characterized by shortening product lifecycles, rising market demands and rapid technological changes (Bowersox et al. 1999, Mallick and Schroeder 2005, Wildemann 2007). As a result, the market window for selling high-technology products is shrinking continuously. In the case of consumer electronics products like cell-phones the profitable market window has in some cases shrunk to less than a year. This situation does not only force companies to shorten their development times (time-to-market) but also the time until they reach full production volume (time-to-volume) in order to meet the financial goals for the product (Terwiesch and Bohn 1998). In addition, rapid time-to-market due to steep ramp-up curves allows firms to recoup development investments quickly (Pisano and Wheelwright 1995), profit from early market opportunities, set technology standards and to accumulate experience with volume production. Also, scarce product development and manufacturing engineering resources can be released and hence support subsequent product development projects instead of solving ongoing production problems.

The period between the end of product development and full scale or unconstrained production is known as production ramp-up (Terwiesch and Bohn 1998, Berg 2007). However, other changes in the production sequence like the introduction of a new process technology or the start-up of a new plant also require ramp-up management efforts. In many ways, these ramp-ups are similar to the ramp-up of new products although additional and to some extent different variables are involved. For reasons of clarity and in order to provide a precise terminology for our subsequent considerations we define product ramp-up according to Wheelwright and Clark (1992, p. 8) as: “In ramp-up the firm starts commercial production at a relatively low level of volume; as the organization develops confidence in its (and its suppliers’) abilities to execute production consistently and marketing’s abilities to sell the product, the volume increases. At the conclusion of the ramp-up phase, the production system has achieved its target levels of volume, cost and quality.”

Ramp-ups are typically characterized by two conflicting factors: low output and high demand. There is high demand because new products offer new and maybe superior functionalities that in turn attract consumers and motivate them to pay premium prices. On the other hand, the output is still low as a result of low production rates, high failure rates and constrained material supply. This aspect has already been presented in various studies covering different industries. Schuh et al. (2005) for example show that 47% of new product ramp-ups in the automotive sector were neither technically nor economically successful. Kuhn et al. (2002) indicate that not a single company in their study claimed to have full control over the production ramp-up. Thus, the ramp-up phase remains a major challenge but it also provides an opportunity to gain a significant competitive advantage.

In this dissertation, we focus on the operational aspects in the domain of operations management. We do not consider the marketing domain that addresses decisions regarding product positionings during the ramp-up phase of new products. Our research aims to understand and explain the phenomena and influential factors with reference to new product ramp-ups and to analyze their implications on performance using qualitative and quantitative information.

1.1 Motivation and Objective

We place our research in the context of consumer electronics, or more precisely, in the context of the cell phone industry. This business sector offers considerable growth rates and profit opportunities. As outlined in Figure 1, the projected growth rates for cell phones – separated into mobile phones and smartphones – are considerable. Compared to mobile phones, smartphones are typically based on a mobile computing platform that offers an advanced computing ability (compared to proprietary firmware commonly found in mobile phones), high-resolution touch-screens, web browsers, advanced connectivity options and sophisticated interfaces that allow for better integration of third-party applications.

In this business landscape, the common strategy to stay competitive and to leverage market opportunities is to develop and introduce top-quality products in relatively rapid succession and on a regular basis. Although the sales volumes outlook for mobile phones is potentially larger than the sales volumes outlook for smartphones their profit margins are considerably smaller as they are primarily sold in developing markets such as China, India, Indonesia, Russia and Brazil. As a result, the ramp-up of mobile phones has to be extremely efficient so as not to jeopardize the tiny profit margins. This requires detailed understanding of the determinants of ramp-up performance.

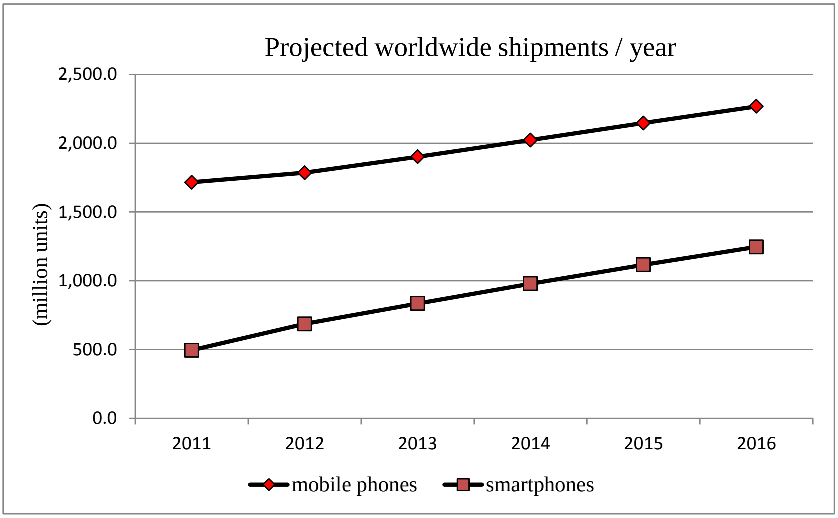


Figure 1. Projected worldwide product shipments (Llamas and Stofega 2012a and 2012b)

Although the literature discusses various influential factors and their qualitative effects on ramp-up performance (Kuhn et al. 2002, van der Merwe 2004, Schuh 2005, Wildemann 2005, Berg 2007) we still know very little about the quantitative and causal relationships between these factors and ramp-up performance. As we show in Table 1, the existing studies on ramp-up management focus on the description of influential factors and on the question how they can be managed. However, existing studies hardly evaluate the implications of product design decisions on ramp-up performance (Krishnan and Ulrich 2001) and the complex relationships between these aspects. In addition, the majority of studies have been carried out in the automotive industry, thus neglecting the specific characteristics and challenges that prevail in the consumer electronics industry. We believe that the examination of ramp-up performance in the consumer electronics industry is particularly interesting because frequent product introductions are very common (i.e., many opportunities for data collection and for empirical analyses). In addition, and compared to other industries, it is an ideal environment to gain insights into the role and behavior of modern software functionalities in new product development. The influence and importance of software content in cell phones, hi-fi systems, game consoles, cameras, MP3 players, flat screens and computer tablets has increased substantially in the past years. This makes it important for product development managers to understand the central role of software in the development of these products and the general effect of software on development lead times and ramp-up performance. In addition, advances in the information and communication technologies will presumably lead to further growth in software content across a wide range of products from other industries as well, hence making it reasonable for development teams in other industries to be aware of the developments in the consumer electronics business.

Table 1. A summary of ramp-up performance determinants

Authors (year)	**Approach**	**Industry**	**Content**	**Key findings regarding ramp-up performance**
Clawson (1985)	None (purely descriptive)	Automotive (Tricycle)	A description of the reasons why manufacturing start-ups go awry from the beginning and how to avoid these pitfalls	Procedures developed for static and consistent programs are too inflexible to support start-ups and generally measure the wrong activity levels. In response, start-up program managers must be comfortable with ambiguous situations, willing to take risks and to communicate openly with a focus on monitoring paths, tooling activities and the right level of control.
Langowitz (1987)	Descriptive-empirical	Information technology	An identification and description of the aspects of new product manufacture and their relationship with the product development process	New product ramp-up performance is positively influenced by: - clear definitions and the use of milestones in the product development process - an atmosphere of high communication standards and transparent coordination - emphasis on product manufacturability adherence to an appropriate product-factory fit
Clark and Fujimoto (1991)	Descriptive-empirical	Automotive	The effect of strategy, organization and management on new product development	Product ramp-up performance is dependent on: - the manufacturing capability - the ramp-up curve - the operation pattern - the work force policy
Terwiesch and Bohn (1998)	Normative-axiomatic	--	Interactions between capacity utilization, yield and process improvement during production ramp-up	There is a tradeoff between production speed and yield/quality. The optimal strategy (speed first or yield first) depends on the relationship between selling price and variable cost.

Authors (year)	Approach	Industry	Content	Key findings regarding ramp-up performance
Terwiesch et al. (1999)	Descriptive-empirical	Consumer electronics	A case study that presents the product transfer from development to an off-shore production facility and ramp-up of hard disk drives and the various forces that allow an organization to increase production volume	Certain organizational patterns increase ramp-up performance: - soft handovers from pilot production to volume production - clear organizational responsibilities together with high commitment and cross functional interactions - the degree to which previous ramp-up experience is leveraged
Almgren (2000)	Descriptive-empirical	Automotive	An examination of disturbances (caused externally or internally) that affect final verification performance and the categorization of these disturbances with reference to their origin in order to gain more control during start-ups	There are certain principles that have a positive effect on the final verification performance: - production systems should always run at full speed to foster the identification of disturbances and improve the rate of learning - organizational support by a temporarily created organization that focuses on effective information processing and disturbance control
Kuhn et al. (2002)	Descriptive-empirical	Automotive, Electrical and Mechanical engineering	An analysis of problems, influencing parameters and processes during the ramp-up period with the objective to provide a structured listing of the most urgent actions and research demands	Five spheres of activity to achieve successful ramp-ups have been proposed: - ramp-up planning and control methods - robust manufacturing systems - ramp-up change management procedures - cooperations and reference models - knowledge management
Vandevelde and Van Dierdonck (2003)	Descriptive-empirical	Different business sectors	Description of major barriers across the design-manufacturing interface and of ways to overcome these barriers in order to achieve a smooth production start-up	Formalization and empathy from design towards manufacturing lowers the negative effects of product complexity and newness and facilitates a smoother production start-up

Authors (year)	Approach	Industry	Content	Key findings regarding ramp-up performance
van der Merwe (2004)	Descriptive-empirical	Different business sectors	Development of a high level conceptual framework that links various forms of novelty to different types of learning which itself drives ramp-up performance	Ramp-up performance is driven by two kinds of learning activities (induced and autonomous) that are in response to four dimensions of novelty (product novelty, process novelty, personnel novelty, supplier novelty)
Schuh et al. (2005)	Descriptive-empirical	Automotive	A conceptual model that identifies successful approaches and concepts for ramp-up management in the automotive industry	Seven areas have been proposed that are relevant for successful ramp-ups: - the ramp-up organization, strategy and planning - ramp-up controlling - disturbance management - engineering change management - supplier and knowledge management
Wildemann (2005)	Descriptive-empirical	Automotive	A summary of solution approaches for successful ramp-up management across the entire supply chain	Outlined concepts: - research areas with reference to ramp-up management - logistical instruments for ramp-up management - ramp-up integration models - knowledge and change management - ramp-up cost controlling
Carillo and Franza (2006)	Normative-axiomatic	--	Theoretical and managerial insights into the crucial linkage between the decisions regarding time-to-market and ramp-up time	The optimal time-to-market and ramp-up time configuration is significantly interdependent. Optimal levels are achieved when the sum of the marginal value of the sales of the new product and the marginal value of the accumulated design knowledge outweigh the marginal value of the sales of the older product generation
Berg (2007)	Descriptive-empirical	Automotive	Identification and categorization of factors that affect production ramp-up performance	From a high level perspective production ramp-up performance is influenced by: - the production ramp-up situation - the product design and the production preparation - the production ramp-up

Most of the existing studies agree on a similar set of influential factors that determine ramp-up performance. In essence, these are:

- physical product characteristics (e.g., product complexity and newness)
- production process and environmental variables (e.g., manufacturing capability, complexity of the production system, level of automation, operation pattern)
- product development characteristics (e.g., formalization, structure and priority, time pressure, priority of manufacturability)
- characteristics of the logistics system (e.g., supply networks and capability, supplier collaboration, material quality)
- organizational characteristics (e.g., cross functionality, roles and responsibilities, work force policy, compensation)
- external factors (e.g., demand fluctuation)

It is important to note that these factors are not isolated but partly interdependent. For example, it is likely to find a bidirectional dependency between product characteristics and production process characteristics as a result of the prevailing in-house manufacturing capabilities and the application of design for manufacturing (DfM) methods during product development. DfM methods may affect the product design in order to increase compliance with the existing manufacturing capabilities. On the other hand, new product designs and innovations are the driving force behind the implementation of potentially new and product specific manufacturing line configurations (although they are often constraint to the prevailing and standardized manufacturing configuration) that largely influence the production process characteristics. A similar dependency can be found between product characteristics and the logistics system. Since suppliers are part of the logistics system, supply networks are dependent on the product concept that largely defines the vertical range of manufacture, the required manufacturing capabilities, the required supply responsiveness and hence, the supplier location for variable parts to enable customization. Conversely, if suppliers are selected from a pool of pre-qualified and approved suppliers the choice may force design engineers to comply with the given technology restrictions and capabilities.

These examples show that there is a variety of influential characteristics with complex interrelationships. However, existing studies have not yet been able to fully integrate them into a comprehensive model. It is our objective to contribute to this limitation in the existing literature with three studies that we have conducted within the cell-phone industry. In our studies we selected, quantified and analyzed a set of characteristics (product, product development process and supply chain structure) that influence the ramp-up process. We also analyzed the interrelationships between these characteristics and their impact on ramp-up performance. Our research is motivated by practical and theoretical considerations. We provide insights and guidelines that offer significant practical value for mangers who are involved in product development and ramp-up management – a topic that is highly relevant in the consumer electronics industry due to the rapid increase in new product ramp-ups. Our contributions should help managers to understand the effects and behaviors of these characteristics on ramp-up performance and hence enable them to cope with the resulting problems in a more efficient way and to find appropriate mitigation strategies for increasingly complex ramp-up problems. Another motivation for this study was to extend the existing body of knowledge regarding new product ramp-ups, because to date a comprehensive theoretical model in this research domain is still missing.

1.2 Research Context

Although the specific problems addressed in this dissertation are of importance for the entire consumer electronics industry they are of particular importance for the cell phone industry. Hence, the problems and challenges related to ramp-up procedures are a key topic for the cell phone business of Nokia Corporation. Nokia is a Finnish public limited liability IT Company headquartered in Espoo, Finland and listed on the stock exchanges in Helsinki, Frankfurt, and New York. In 2012, Nokia employed approximately 122,000 employees across 120 countries and Nokia products were sold in more than 150 countries, creating annual revenues of around €38 billion (Nokia Corporation 2012).

Nokia offers mobile communication products, services and software related to mobile devices as well as navigation services through its subsidiary Navteq. In addition, Nokia offers online services and software including applications, games, music, maps, media and messaging services that are distributed through the company’s own Ovi platform. In a joint venture with Siemens, Nokia also provides telecommunications network equipment and services under the name of Nokia Siemens Networks.

Nokia used to be the largest global vendor of cell phones from 1998 to 2012 but over the past years it has suffered declining market shares as a result of the growing use of smartphones and its uncompetitive product portfolio in this segment. In response to this changing market situation, Nokia has entered into a strategic partnership with Microsoft. As a result of this partnership all new Nokia smartphones incorporate Microsoft's operating system *Windows Phone* while Nokia’s mobile phones continue to use a proprietary operating system called *Series 40*.

At Nokia, the development of a new product always follows a similar sequence of actions. First, the company chooses an R&D center based on criteria like the best fit between center-specific competences and the product mission, estimated sales volume and customer base. In a second step, a cross functional project management team is allocated that consists of project managers from R&D, marketing, sourcing, production, customer service and product validation. All subsequent development activities follow a highly structured milestone controlled development process. The process starts with a detailed planning and conception phase in which technology developments, market objectives and several different concepts are evaluated. In the following, the most appropriate concept for further development is selected and the actual design phase begins. During this phase, the complete product specification is created and all product specific and common components are identified based on make-or-buy analyses.

In contrast to common components that are ready-made and purchased from suppliers, product specific components typically require additional tooling equipment and in-house development work. The manufacturing process map that specifies how the product is manufactured, assembled and tested is also established at this point of the development process. At the same time multiple prototypes of the product are manufactured and tested. Consumer electronics products are often developed according to a spiral product development process. Since the building and testing of prototypes has become a rapid process the design-build-test cycle can be repeated many times (Ulrich and Eppinger 2008). Prototypes are created on dedicated pre-production lines and manufactured using processes that are very similar to mass-production. The purpose of prototyping is to determine whether the product works as planned in terms of performance and reliability and whether the manufacturing process is robust enough and capable to deliver the planned quantities during the mass production phase. In parallel to these activities, a concomitant software development process delivers new software packages for each new prototype cycle. Software management, development and stabilization (software error detection, correction and verification) have become major activities in new cell phone projects as more and more features are implemented via software. After a clearly defined set of deliverables regarding the new product has been achieved and approved by the steering group and after key customers have approved the software configuration the "start of production and sales" project milestone can be granted. Now, the lead factory ramp-up phase begins which is defined as the time between the project milestone "start of production and sales" and the moment when production output switches from a predefined push plan that is based on sales estimates – as exact customer orders are not yet known – to a pull plan that is consumer demand driven. During that phase, the output is successively increased until it reaches a stable level. This gradual increase serves as an opportunity to train the workforce, eliminate remaining problems in material supply, material quality, product design and in the production process. Depending on the total sales volume level, additional factories and supply networks may be introduced at a later stage when most of the initial problems are under control. In contrast to many other companies, Nokia applies a shutdown approach concerning the operational pattern. In other words, existing products are always ramped-down before new products are ramped-up on the same but converted manufacturing lines. A simplified representation of such a manufacturing line is shown in Figure 2. This line configuration is applied across most of Nokia's production plants and even copied to contract manufacturing plants that are part of the manufacturing network. As a result the in-house manufacturing depth is homogeneous throughout this study. The production process starts with the assembly of the logic board called SMT (surface mount technology). During this phase all electrical components of the logic board are assembled and soldered in an automated process. The assembly of the logic board is followed by a first test phase that adds test software to the board in order to perform basic functional tests and to align the radio frequency module. This procedure is necessary as hardware components have a rather wide tolerance range while the radio frequency parameters have to meet relatively tight legal requirements. Before the assembly work begins the auxiliary-flaps on the logic boards – that have been necessary for the handling in the previous process steps – have to be removed by means of a milling process. During the final assembly step the logic board and other electromechanical parts are assembled into the mechanical covers. Depending on plant location and automation strategy the assembly is either conducted in a manual, semi-automated or fully automated process. Finally, the assembly is followed by an additional functional test phase to control the production process and to avoid the shipment of non-conforming units. A packing process prepares the semi-finished units for shipping to the customization centers in which the customer specific configurations take place.

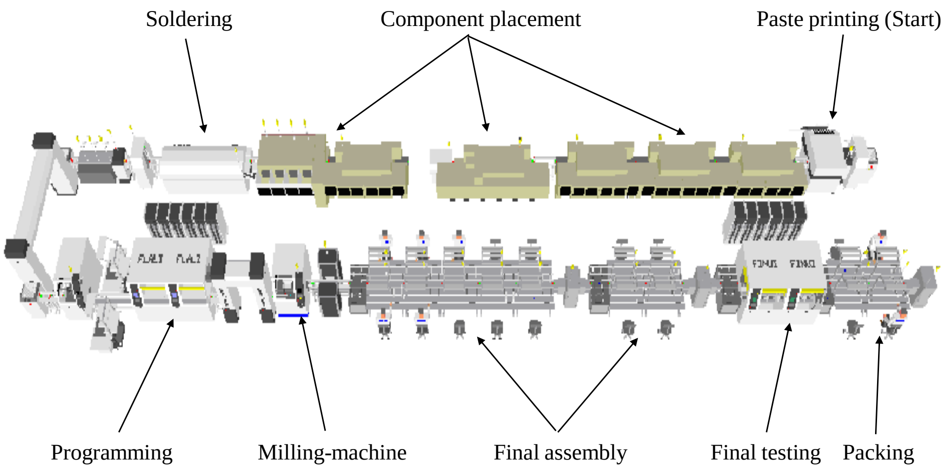


Figure 2. A simplified representation of a manufacturing line configuration for cell phones

1.2.1 Data Collection

Our research uses the individual cell-phone developed by Nokia as the unit of analysis for which we gathered detailed qualitative and quantitative data. In comparison to a theoretical or biased sampling approach – common in case study research (Barratt et al. 2011) – we drew random samples from the population. We selected every fifth product in the sequence from a product list that contains all products in an approximate temporal order. This approach reduced the risk of sample interdependencies while ensuring for sample diversity. Our database contains data on 46 products which represent around 20% of the population from four development sites during the sampling interval (2005 - 2008). We only excluded projects that did not follow a complete development cycle such as product life cycle extensions via color, component or software updates and three products that only provided incomplete datasets. As the author is employed as a ramp-up manager at Nokia we had access to various databases, project documentation files, management information system reports, data archives and even confidential information such as material costs, product profits and sales figures. The only limitation to our data collection method was the inability to include characteristics that are not listed in existing reporting systems such as soft factors like motivation, experience, workload, cultural factors or characteristics that are either extremely difficult to quantify and multidimensional in nature (e.g., strategic choices). Please refer to Appendix-D1 for a detailed overview of the variables that were used in this research project and their respective sources. We additionally developed a written questionnaire to capture qualitative ramp-up management information for the respective product ramp-ups in order to provide substantiated explanations in connection with our formal analysis. For this purpose, we contacted the respective ramp-up managers and explained the purpose of the provided questionnaire. As part of the product development management team, ramp-up managers are key information sources as they possess comprehensive knowledge about the various issues that happen during product development and production ramp-up. After a period of one week we contacted the respondents again to collect the information. During the scheduled discussion, we reviewed the provided information and added potential supplementary information. As a result of this structured process, we achieved a return rate of 100%. Detailed information on the questions of the questionnaire is provided in Appendix-D2. We were also able to collect longitudinal project data and triangulated all data with mandatory milestone review documents. Such an empirical scope (i.e., single firm context) offers particular advantages as it allows us to control for various environmental specific effects. Thus, we only needed to control for variables that show measurable variance within our context. Given the relatively small sample size of our study, we performed a power analysis with G*Power 3 (Faul et al. 2007) to evaluate whether our statistical tests (given a population effect size, sample size and alpha level) can detect any significant effect when one truly exists. In other words, we wanted to identify the error probability β associated with a false decision in favor of the H_0 (Faul et al. 2007). We summarized the power of our statistical tests as a function of the number of predictors and different effect size specifications for the underlying population in Table 2. Statistical power levelsTable 2. According to the results from G*Power 3 (Test family = F test; Statistical test = Linear multiple regression: Fixed model, R^2 deviation from zero), the statistical power of our models, - given a specified medium population effect size - ranges from 0.35 (most complex model) up to 0.67 (least complex model). As we point out in our chapter specific methodology sections in more detail we typically started our modeling process with a small number of predictors in different combinations and subsequently increased the complexity of our model in order to maximize the statistical power.

Table 2. Statistical power levels

	Population effect size		
Number of predictors	0.02 (small)	0.15 (medium)	0.35 (large)
3	0.18	0.67	0.95
5	0.16	0.57	0.91
6	0.15	0.54	0.89
7	0.15	0.50	0.86
8	0.14	0.47	0.83
11	0.13	0.40	0.76
14	0.13	0.35	0.69

With this context in mind, we now present the main research questions and the contributions of this dissertation in the next section.

1.3 Research Questions and Methodologies

This dissertation aims at quantifying product, product development process and supply chain structure characteristics that influence the ramp-up phase and at analyzing their influence on different metrics of ramp-up performance. In addition, we strive to find an explanation for the mechanisms behind these effects with the help of our comprehensive database. This should provide us with a substantially enhanced and more detailed understanding of the entire ramp-up process. In order to achieve this objective we raise a number of research questions that will address these items in the upcoming chapters. Our research design was primarily driven by our objective to produce reliable in-depth analyses of characteristics determining ramp-up performance, to provide predictive capabilities for real world product ramp-up situations and by our unique access to operational data and supplementary qualitative information. Based on this highly reliable quantitative and qualitative data we decided to use ordinary least squares (OLS) multiple regression analysis and partial least squares (PLS) path modeling as the dominant statistical methodologies. Both methods provide slightly different but complementary information for the identification of those characteristics that are important predictors of ramp-up performance. In addition, PLS allows for the estimation of a sequence of separate multiple regression equations successively in order to analyze structural and mediator effects. Next, we will discuss the individual research questions in more detail and outline their respective rationale.

1.3.1 The Impact of Product Complexity on Ramp-up Performance

First, we identified and selected the key determinants of ramp-up performance based on our literature review in order to achieve our goal of an enhanced understanding of the factors that influence this process. We also needed to find out how they can be operationalized in a rigor way that allows the use of statistical techniques. As there is consensus in the literature (Table 1) that product characteristics in terms of product complexity are one of the major determinants of ramp-up performance we started our research work with the inclusion of this dimension. In most cases, product complexity is considered in physical terms and as a property of a product (Rodriguez-Toro et al. 2004). However, the increasingly dominant role of software in modern consumer electronics products and the impact of software on complexity and development schedules make it necessary to include software as an additional key distinctive factor in the definition and quantification of product complexity. Therefore, the identification of relevant product characteristics (hardware and software aspects) and their quantitative definition is the first step in our research leading us to our first research question:

I. *How can product complexity characteristics of consumer electronics devices, and specifically of cell phones, be modeled in quantitative terms?*

To address this question in chapter 2 we develop measures for hardware and software complexity based on an extensive literature review. We identified the work of Novak and Eppinger (2001) to be the most applicable source for our study. In simple terms, they measure hardware complexity as the number of components, the level of interactions between these components and the degree of novelty. In order to provide a definition for our software complexity measures we follow the structure of our hardware complexity definition and proposals from the software engineering literature. Hence, we consider the number of lines of code (counterpart of component count), their newness (counterpart of novelty) and the occurring errors as appropriate measures for software complexity. We apply error count as a proxy for software coupling since we encountered limitations in our data collection process regarding software coupling measures and error count strongly correlates with existing software coupling measures (Henry and Kafura 1981, Troy and Zweben 1981). Also, error count has a strong managerial relevance as early and continuous estimations of error count allow for risk assessments and predictions (i.e., the remaining development effort) – a prime focus of our study. In a next step we collected data for these characteristics and started to perform multiple regression modeling in order to find a model that provides a fit between the conceptual/theoretical domain and the statistical significance. Finally, we discuss the direction and strength of the interactions between these characteristics.

Following this, we analyze how these product characteristics affect ramp-up performance, specifically manufacturing and total product ramp-up performance. At first, we identified as set of measuring units for manufacturing ramp-up performance since we hypothesize that customer shipments cannot start until the manufacturing system is ready and capable to supply products. In line with existing studies on ramp-up management we apply a combination of final yield and utilization to analyze the effect of product complexity on manufacturing ramp-up performance. Total product ramp-up performance on the other hand is operationalized based on the idea of value creation. In other words, we consider the dependable delivery of products – provided they fulfill the set quality criteria – as a significant driver of customer value and ultimately total product ramp-up performance. Altogether, this set of manufacturing and total product ramp-up performance variables along with the complexity characteristics provides the basis for our second research question:

II. How do product complexity characteristics interact with each other and subsequently influence manufacturing and total product ramp-up performance?

We address this question in chapter 2 and in parts also in chapter 3. In chapter 2 we analyze the effect of every individual complexity variable on the performance variables. Using a set of ordinary least squares (OLS) regression models we gain insights into the coupling between the hardware and software variables and regarding the individual effects of these variables on manufacturing and total product ramp-up performance. In chapter 3 we examine the interaction between hardware and software characteristics and their impact on manufacturing ramp-up performance again but now with the help of a partial least squares (PLS) path modeling approach that can be considered as a multivariate extension of OLS. In fact, the iterative algorithm in PLS generally consists of a series of ordinary least squares analyses (Chin 1998). The application of this method provides us with additional insights on top of the previously performed regression models as PLS regresses constructs (an unobservable concept that cannot be measured directly but is represented by a set of weighted variables (Hair et al. 2006)) on constructs to estimate the path weights while OLS regresses variables on variables. In addition, PLS estimates all parameters at once and the presence of other parameters is taken into account by the algorithm. Therefore, this non-fragmented approach allows us to additionally explore the mechanism via which complexity harms manufacturing ramp-up performance (mediator effects).

1.3.2 How does Development Lead Time affect Performance over the Ramp-up Lifecycle?

As already mentioned, pure ramp-up performance is not the only crucial consideration for high technology firms. It is equally important to implement efficient processes for the development of new products in order to reach the ramp-up phase as quickly as possible. However, most of the studies in this field have examined product development process characteristics such as development lead time (time-to-market) and ramp-up performance (time-to-volume) separately, while their significant interrelationship has received only little attention (Terwiesch et al. 1999, Gerwin and Barrowman 2002). In addition to the product characteristic variables (product complexity), we hence include product development process characteristic variables (i.e., development lead time) in our framework to assess the interactions between these variables and their simultaneous impact on manufacturing ramp-up performance. In addition, we are interested in how the behavior of this model changes during the ramp-up lifecycle. The ramp-up lifecycle marks the various phases from the initial start, characterized by a chaotic and dynamic environment up to the transition into mass-production that is characterized by diminishing ramp-up specific difficulties and an increasing influence of factors that are related to mass volume production. We believe this information is crucial for managers to anticipate the consequences of product design decisions on development lead time, to predict development schedules and in order to make informed decisions about ramp-up volume commitments during the various ramp-up lifecycle phases.

III. *What are the interrelationships between product characteristics (product complexity), product development process characteristics (development lead time) and manufacturing ramp-up performance over the course of the ramp-up lifecycle?*

Chapter 3 is devoted to the detailed analysis of this research question. As already mentioned above, we use a variance based structural equation modeling approach known as PLS path modeling in order to analyze the interdependencies between the selected variable blocks and manufacturing ramp-up performance. Compared to covariance based structural equation modeling approaches (e.g., LISREL), PLS is particularly well suited for our study since we use operational data and our primary research objective is the maximization of explained variance in manufacturing ramp-up performance (i.e., prediction) instead of achieving model “fit” as in theory testing. Our data partly violates the requirement of multivariate normality and our sample size is limited to the available amount of real life cases. PLS, however, does not make any assumptions of the underlying distribution and provides stable estimates even if the ratio of observations to parameters is small (Wold 1982, Fornell and Bookstein 1982, Chin 1998, Hair et al. 2011). As we are also interested in the behavior of our PLS model over the ramp-up lifecycle, we have collected performance data for five different time horizons (4, 8, 12, 16, 20 weeks). In a next step we analyze the different results and sort them in a time dependent way. This allows us to provide plausible explanations for the time-dependent influence of the different complexity variables and development lead time variables and the resulting consequences for manufacturing ramp-up performance.

1.3.3 Uncovering Plant Specific Differences during New Product Ramp-ups

With our last research question we want to complement our insights into the ramp-up process by investigating the effect of supply chain structure specific characteristics. This area has been mentioned as highly influential on ramp-up performance in the literature (Langowitz 1987, Clark and Fujimoto 1991, Terwiesch et al. 1999, Almgren 2000, Kuhn et al. 2002, Wildemann 2005, Berg 2007) but detailed quantitative empirical studies are sparse. In addition, considerable work packages have to be handled during new product ramp-ups within the factories and at key suppliers. It is thus a logical consequence to include these characteristics in our existing ramp-up framework. We want to relate quantitative supply chain structure characteristics to manufacturing ramp-up performance in order to fill the gap that exists in the literature and to support product development and operations managers in their decision making. In addition, we expect these characteristics to uncover plant specific effects like performance differences or issues regarding the fit between product characteristics and plant/supply networks. Accordingly, we state our last research question which is analyzed in chapter 4:

IV. What supply-chain structure characteristics uncover plant specific effects in the context of manufacturing ramp-up performance?

In a first step, we reviewed the literature in order to identify the most applicable supply chain structure characteristics that are prevalent within our context. Then we operationalized the selected characteristics and subsequently collected the relevant data. Using OLS regression we analyzed the impact of the selected variables while controlling for the effect of product complexity and development lead time. The question which supply chain structure characteristics have the most crucial impact during new product ramp-ups was of particular interest because this information is strongly required for various managerial decisions like e.g. the selection of the most appropriate lead factory. It is important for managers to know whether they can profit most from supply proximity (via short feedback loops), proximity of supplier engineering capabilities or factory capabilities.

1.4 Outline of the Dissertation

We summarized the different research questions and how they are addressed in the dissertation in Table 3. Each chapter is self-contained and can be read independently. The content presented in chapter 2 also appeared in Pufall et al. (2012a) and the analyses described in chapter 3 appeared in Pufall et al. (2012b).

Table 3. Dissertation outline

Chapter	**Overall focus**	**Main factors assessed**				
		Product complexity	Development lead time	Operations characteristics	Supply characteristics	Ramp-up time horizon
2	Product characteristics	X				12 weeks
3	Product development process characteristics	X	X			4, 8, 12, 16, 20 weeks
4	Supply chain structure characteristics	X	X	X	X	12 weeks

Chapter 2

The Impact of Product Complexity on Ramp-up Performance[1]

Abstract: *This chapter identifies the key product characteristics that affect ramp-up performance using operational data from the cell phone industry. We investigate three research questions: (1) How to measure software and hardware complexity characteristics of consumer electronics products – and specifically cell phones? (2) To what extent drive product complexity characteristics manufacturing ramp-up performance? and (3), in turn, to what extent drive manufacturing ramp-up performance and complexity characteristics total product ramp-up performance? The findings contribute to operations management literature in three ways: First, our model reflects the growing importance of software characteristics in driving hardware complexity, an aspect that prior empirical ramp-up studies have not yet addressed. Second, specific hardware characteristics (i.e., product specific component count and parts coupling) primarily drive the performance of the manufacturing system in terms of final yield and effective utilization. And finally, effective utilization together with the novelty aspects of both software and hardware complexity (i.e., SW novelty and product novelty) are the key determinants of total product ramp-up performance.*

[1] The results in this chapter have also been presented in Pufall et al. (2012a).

2.1 Introduction

New product development (NPD) is particularly challenging in the high-technology sector, increasingly characterized by shortening product lifecycles, rising market fragmentation, and rapid technological changes (Bowersox et al. 1999, Mallick and Schroeder 2005, Wildemann 2007). If firms want to succeed in this environment, they must be effective and efficient in their introduction of new products or product updates. According to Bowersox et al. (1999), new product introductions involve two major activities: product development (conceptualization, design, promotion, and pricing) and product launch (physical positioning in the market). Traditionally, the marketing literature has addressed positioning decisions (Cooper and Kleinschmidt 1995, Bowersox et al. 1999, Benedetto 1999) whereas the operations management literature has considered supply chain decisions (Clark and Fujimoto 1991, Tatikonda and Montoya-Weiss 2001).

In this study, we adopt an operations management perspective and focus on the final phase of the NPD process, namely, the ramp-up phase. This phase links product development to mass production, or as Wheelwright and Clark (1992, p. 8) detail: "In ramp-up the firm starts commercial production at a relatively low level of volume; as the organization develops confidence in its (and its suppliers') abilities to execute production consistently and marketing's abilities to sell the product, the volume increases. At the conclusion of the ramp-up phase, the production system has achieved its target levels of volume, cost and quality." Yet many companies fail to meet their targets regarding product volume, cost, and quality. Schuh et al. (2005) show that 47% of automotive new product ramp-ups were neither technically nor economically successful. Kuhn et al. (2002) indicate that not a single company in their study claimed its production ramp-up was under control. Thus, the ramp-up phase remains a major challenge, even as it provides a significant opportunity for competitive advantages. In addition, the complex relationships that constitute the ramp-up phase have been investigated only partially and insufficiently developed (Kuhn et al. 2002). Therefore, there is strong motivation to gain a more thorough understanding of the influential factors that affect the ramp-up phase and how they relate to success or failure. Previous studies have identified several factors that affect ramp-up performance (Table 1). Clark and Fujimoto's (1991) global field study in the automotive industry reveals that the transition management between new and existing products (ramp-up scenario), the rate of production in terms of line speed, the number of products in the line and the operation time per day (operational pattern) as well as the manufacturing capabilities relate closely to superior product development and ramp-up performance. In addition, Pisano and Wheelwright (1995) reinforce the link between manufacturing process innovation, productive product launches and enhanced product functionalities. In their large German case study, Kuhn et al. (2002) confirm the importance of manufacturing and logistics capabilities and further identify the product, organization, cooperation and the tools used as crucial factors for ramp-up success. To analyze the types and sources of disturbances that affect manufacturing start-up phases, Almgren (2000) categorizes the different sources into four groups: product architecture, material flow, production technology, and work organization. A longitudinal study in the data storage industry also reveals organizational patterns and suggests that previous ramp-up experience, such as through product platforms, influences the ramp-up of new products (Terwiesch et al. 1999). Langowitz (1987) observes that the success of ramp-ups depends on the management of the development process and how well the requirements of the new product and factory capabilities fit together. Finally, van der Merwe (2004) proposes a conceptual model that supports the association between different types of novelty (product, personnel, supplier, and process) and learning types that drive ramp-up performance.

Despite these multiple studies that have identified a vast number of influential factors, we know very little about the quantitative and causal relationships between these factors and ramp-up performance. Krishnan and Ulrich (2001) argue that essentially no work has investigated the relationship between product design decisions and the rate of production ramp-up. In response, we use operational data (for the research setting refer to section 1.2) to develop new quantitative measures for these factors and extend the current understanding of product attributes by including software-related elements to investigate three general research questions: (1) How to measure software and hardware complexity characteristics of consumer electronics products – and specifically cell phones? (2) To what extent drive product complexity characteristics manufacturing ramp-up performance? and (3), in turn, to what extent drive manufacturing ramp-up performance and complexity characteristics total product ramp-up performance?

The remainder of this chapter is organized as follows: in the next section, we present our conceptual model. After the formal presentation of our Hypotheses in section 2.3 and the illustration of our data and methodology in section 2.4, we present our results. In section 2.6, we discuss our results and provide managerial insights and conclude with some limitations of this particular part of the study and implications for further research in section 2.7.

2.2 Conceptual Model

Our conceptual model as shown in Figure 3 suggests that manufacturing and total product ramp-up performance depend on the level of product complexity, which we define in terms of software and hardware complexity. While our conceptualization of complexity is consistent with existing literature, it represents a refinement because it reflects the growing importance of software in a product development and ramp-up context, a topic that was generally ignored in prior empirical ramp-up studies (e.g., Langowitz 1987, Almgren 2000, van der Merwe 2004).

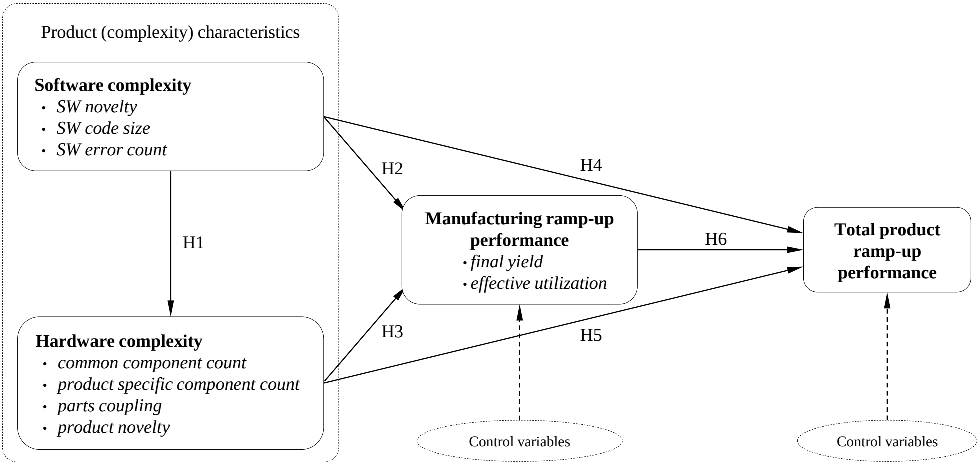


Figure 3. Conceptual model

Before we state our Hypotheses we first introduce the variables that constitute our conceptual model.

2.2.1 Software Complexity Variables

With the term "software", we refer to the operating software and any application software under the direct control of the firm, which gets programmed into the logic board of the product during the production process and is entirely necessary for a successful launch. We do not include software modules or subroutines that are an inseparable part of any advanced component or application software from third-party suppliers. For example games, special ring tones, or other third-party applications can be introduced in subsequent software releases if they are not on a sufficiently mature level at ramp-up start. In contrast, in-house developed core-software elements must be available and error free for product launch, such as operating software functions (e.g., protocol stack routines). Errors in such functions may prevent regulatory approvals and potentially delay the ramp-up phase.

Generally, software complexity refers to the characteristics of the data structures and procedures within the software that make it difficult to understand and change (Curtis et al. 1979, Zuse 1991). Many software engineering studies rely on code and structure metrics as quantitative measures of software complexity. The former entail the individual system components (procedures and modules) and require detailed knowledge of their internal mechanisms, whereas the latter consider the product as a component of a larger system and focus on the interconnections of the system components (Kafura and Reddy 1987, Banker et al. 1998). However, previous research into multiple proposed software complexity metrics indicates high correlations among the various metrics (Banker et al. 1993, Munson and Koshgoftaar 1991). Our analysis has revealed three major groups that vary in different orthogonal dimensions and thus overcome this limitation: SW novelty, SW code size, and SW error count. Due to the fact that software development is standardized within Nokia, it allows for the collection of reliable data regarding these software characteristics.

First, *SW novelty* represents the number of new requirements/features in the software specification for each product and is derived from the requirements management database. Understanding and managing new functions, for which the behavior and interactions with other elements is not known in advance, adds uncertainty, risk, and effort to the team's responsibilities, which could provoke difficulties before and during the ramp-up phase. Krishnan and Zhu (2006) claim that adding more features usually increases complexity and reduces the software's ease of use. On the other hand, existing software code that gets used and tested across many products, all else being equal, should have greater design integrity and quality than new software code developed for a single, particular product. Therefore, we posit that the greater use of new software elements influences the integrity of the existing software structure and increases risks related to on-time readiness. In our study, SW novelty therefore refers to the number of new software features/requirements for the product that are not used by any other product. In other words, it is the number of new features in a cell phone that have not been included in previous products or the existing software baseline.

Our second software complexity variable measures the source *SW code size* in terms of executable lines of code as provided by the compiler log files. Source code size metrics, though common ways to describe software complexity, are particularly important in embedded systems that suffer from memory restrictions. Although software engineering literature often uses a lines of code measure, its problems are well known (Krishnan et al. 2000), especially related to the inaccurate and inconsistent definition of "a line of code" in various programming languages and the tools used to count the number of source lines. To ensure the consistency and accuracy of this measurement across products, we used a common analysis tool that measures the number of lines of executable code. According to Krishnan et al. (2000), counting executable statements offers a more accurate measure than counting the number of physical lines. Because the products in our sample share the same programming languages (i.e., a proprietary language for lower-level signaling functions and C/C++ for higher-level code) and are based on the same programming tools, our measure of SW code size is not biased by the programming language or environment.

Finally, and because SW novelty and SW code size do not sufficiently account for coupling effects, we include *SW error count* as a proxy for coupling effects to our software complexity framework. Even a small share of SW novelty and small SW code size can lead to a disproportionate amount of development effort if the respective configuration results in a large number of errors due to interactions and side effects. SW error count strongly correlates with existing software coupling measures (Henry and Kafura 1981, Troy and Zweben 1981) and accounts for differences in the individual product configuration, as both SW novelty and SW code size assume that software components have built-in complexities that are static and independent of their context. In addition, and unlike other metrics (e.g., McCabe's (1976) cyclomatic complexity, Wood's (1986) component/coordination/dynamic dimensions, Halstead's (1977) effort metric), SW error count has a strong managerial relevance since it can be estimated *a priori* during the later development phases to assess the prevailing development risk and to predict the remaining development effort. It is also used by management as a means to monitor product maturity. Consumer electronics products must typically pass a series of standardized software acceptance tests hence SW error count can reveal the actual progress in the software development process and the readiness for product launch. We measure it as the number of reported errors during the software acceptance/verification phase.

2.2.2 Hardware Complexity Variables

To quantify hardware complexity we consider products in physical terms and hence assume complexity to be a property of the product (Rodriguez-Toro et al. 2004). According to Novak and Eppinger (2001), it can be measured as (1) the number of product components to specify and produce, (2) the extent of interactions to manage between these components (parts coupling), and (3) the degree of product novelty. Please note that we consider hardware complexity at the macro level, that is, the first layer of abstraction, which is under managerial control and technically observable. We do not consider the internal structures of the lower levels (e.g., subsystems, advanced components) such as cameras, displays, or speakers.

Our first hardware complexity variables – *common component count* and *product specific component count* - cover the total number of components in a cell phone as reported in the product data management system (see Table 4). The division of component count into two parts allows for the identification of the relevant components in the context of ramp-up performance. *Common component count* comprises all components from the product's bill of material list like resistors, capacitors, transistors, connectors, shields and integrated circuits which are assembled onto the printed wiring board. These components are freely available on the market and hence also used in other products from the case company or competitors. *Product specific component count* refers to components in the bill of materials list that are specifically developed for the use in a dedicated product. Hence, the options to use these components in other products or industries are very limited. Examples are plastic covers, antenna elements, stickers, foams, gaskets, displays and cables. Please note that this definition does not include components that are inseparably embedded in advanced components, such as the single glass layers of display modules or the individual lens elements in camera components. The increasing variety in component count results from the growing diversity in the cell phone customer base which forces companies to offer tailored models with various functionality levels for different target groups. However, these different functionalities cannot be integrated into the same basic product architecture without altering the number of necessary components (whether common or product specific). A product that offers dual display functionality, hands-free stereo audio, global positioning services (GPS) and sophisticated connectivity options must integrate more physical components into its architecture than a featureless counterpart. Adding more components to a product raises product complexity in terms of a more difficult manufacturing process (Boothroyd et al. 1987, Coughlan 1992), more complex supply logistics (Fisher et al. 1999) and greater verification effort (Novak and Eppinger 2001).

For our *parts coupling* variable, we note that modern cell phones exhibit diverse interdependencies among the embedded components. As Novak and Eppinger (2001) state, the more interconnected the parts in a system are, the more difficult it is to coordinate their development. To quantify the level of parts coupling, we use the report functionality of a circuit board design tool and count the number of signal networks across all electrical and electromechanical components in a product, (i.e., components that carry any electrical functionality like resistors, capacitors, integrated circuits, antennas, audio components). This group of components accounts for more than 70% of the total components in a product. Our rationale for this definition of parts coupling stems from discussions with R&D experts, who confirmed that the effective integration of components does not only require knowledge about the components but also about their simultaneous interactions. Many components are delivered fully functional and pretested, hence the key challenge of development lies in the mastering of coupling effects. Measuring the number of networks is a more reasonable approach to account for the difficulties that developers encounter than measuring the number of pairs (i.e., direct connections between electrical and electromechanical components). Development engineers must consider the electrical structure of the various subsystems as an arrangement of interlinked connections rather than a collection of individual point-to-point connections. The number of networks also is unbiased with regard to those aspects that increase pair count (e.g., test points) without adding interaction complexity.

Finally, the existing literature has conceptualized product novelty in several ways. Coughlan (1992) defines newness as the degree of similarity of a product to other members of its family, or the degree to which preexisting product parts get altered. Swink (1999) refers to newness as the percentage of new designs in the product. We build on these definitions though we use a richer operationalization: we define *product novelty* as the percentage material value of physical components in a cell phone that is new to the responsible development center, compared with previous products that have already been developed at this development center. Our observations have led us to conclude that this percentage material value offers a better operationalization than the percentage number of new parts – especially considering our macro perspective that considers certain advanced components (e.g., cameras, displays, speakers) as single components. Thus, definitions of product novelty that are based on the percentage of new parts regard each component’s contribution to novelty as equal, even though new displays, cameras, or processors require considerably more effort during integration and testing phases and entail more supply risk during the ramp-up phase than simple parts like new screws, foams, or stickers. This variance in complexity within single components supports our use of their monetary value as a measure of product novelty. Based on the officially filed product development documentation and specification we were able to identify all lead components for each product. Together with the sourcing parts list we were consequently able to calculate the product novelty measure.

2.2.3 Manufacturing Ramp-up Performance Variables

Despite the many proposals on how to quantify manufacturing performance (Neely et al. 1995, White 1996, Slack et al. 2001, de Toni and Tonchia 2001), most of the ramp-up specific studies use capacity and/or final yield measures (Matsuo et al. 1997, Terwiesch et al. 1999, Hatch and Mowery 1998, Almgren 2000). We follow this approach and use *effective utilization* together with *final yield* as variables to measure manufacturing ramp-up performance. This combination acknowledges that the actual output of any manufacturing system is only a fraction of the planned allocated capacity (see Figure 4) and the particular type of lost capacity may be of importance (e.g., yield losses may be different from other losses as they can be reworked and fed back into production).

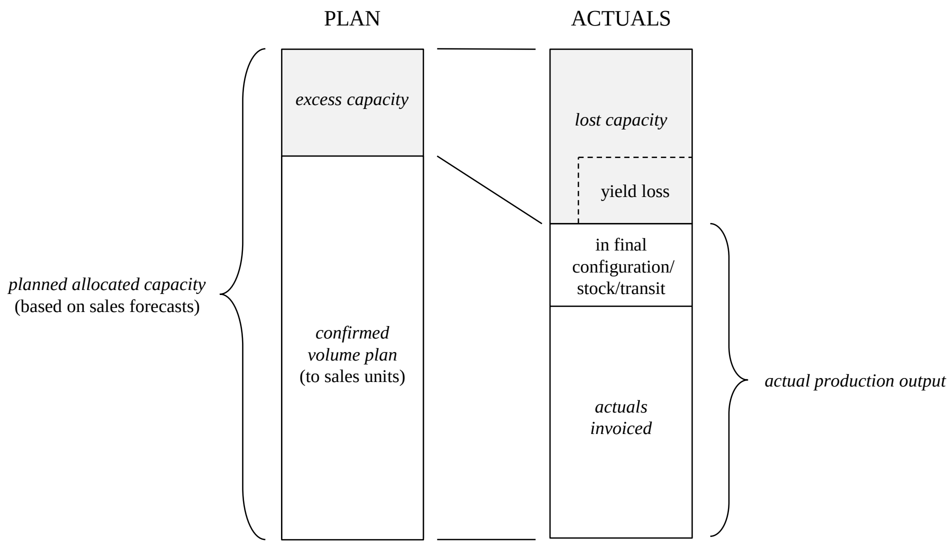


Figure 4. Determinants of manufacturing ramp-up and total product ramp-up performance

Final yield. In consumer electronics, manufacturing usually takes place on multistage production lines with different control or test phases. Typically, a first test phase takes place after the components are installed on the circuit board (i.e., commonly known as the logic board). The series of electronic tests at this point ensure that the circuit board is functional, that all parts are operational, and that all parts are correctly installed. Yield losses at this stage relate to soldering defects, material deficiencies and test system failures. After this stage, the assembly work begins and electromechanical parts are added to the circuit board before it is mounted between structural frames and undergoes a detailed functional test. Yield losses at both test phases identify product and process instabilities, which is why *final yield* frequently appears in manufacturing literature (Hatch and Mowery 1998, Terwiesch and Bohn 1998, Terwiesch et al. 1999, van der Merwe 2004, Keil et al. 2007).

Effective utilization is quantified as 1 minus the ratio of lost capacity to its planned allocated capacity. Although capacity measures are subject to criticism for its negative long-term implications (Slack et al. 2001, Goldratt and Cox 2004), effective utilization is sensitive to ramp-up specific disturbance factors that may result in various capacity losses, such as product and equipment readiness issues, product manufacturability concerns, material availability/quality problems, unscheduled engineering trials, or neglected operator training. Ultimately, these disturbance factors have a negative influence on effective utilization because they impede that the entire allocated capacity can be used to manufacture end products. Effective utilization and final yield are both based on data from a production database system and their calculations are summarized in Table 4.

2.2.4 Total Product Ramp-up Performance

According to Mallick and Schroeder (2005), high-tech firms use their technology to create value for their customers and to capture value for their shareholders. Thus, any metric used to measure total product ramp-up performance in high-tech manufacturing should reflect the objective of value creation. In line with existing studies that focus on time, cost and quality (Kuhn et al. 2002, Schuh et al. 2005, Wildemann 2007); quantity, cost and quality (Almgren 2000); or missed targets for output, quality and delivery (Langowitz 1987), we posit that all activities surrounding the dependable delivery of products – provided they fulfill the set quality criteria – are significant drivers of customer value and hence total product ramp-up performance for high-tech products. Dependable sales volume deliveries are particular crucial before seasonal peaks (e.g., Christmas or the Chinese New Year) when strong consumer demand must be satisfied in a very short period of time (possibly at the expense of higher unit costs, compromises on inventory levels, or manufacturing effort) as lost sales and customer loyalty cannot be recaptured at a later phase. Hence, we measure *total product ramp-up performance* as the actual invoiced quantity during the ramp-up execution phase divided by the confirmed volume plan quantity for the same period. In other words, we measure sales volume fulfillment rather than absolute ramp-up speed. According to Voigt and Thiell (2005) the focus on pure ramp-up speed is economically inefficient, because quality and other cost drivers may accumulate and ultimately affect overall company competitiveness. Ramp-ups with expansion rates greater than planned may reveal strong output performance but do not necessarily contribute to profitability or increased value creation if they only fill outbound buffers. For the ramp-up execution phase (T_{RU_EXE}) we chose a time horizon of 12 weeks since it reflects the (product-independent) short-term planning cycle that prevails at Nokia. During this time frame, capacity and most resource availability is considered fixed, because of equipment and material procurement lead time limitations. We detail this period in Figure 5.

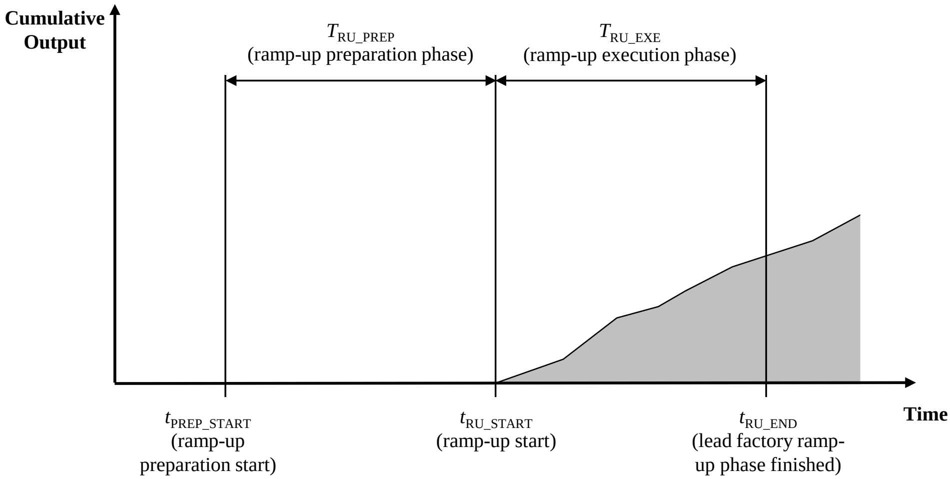


Figure 5. Ramp-up phase time parameters

2.2.5 Control Variables

First, we include a control variable that captures linear time effects. Consistent with learning curve studies, we define learning as the increase in ramp-up performance by a firm as its experience increases over time. We must differentiate between learning from experience and changes in ramp-up performance independent of experience, hence we include a *linear trend* control variable, which is the number of days between the ramp-up start of each product versus the ramp-up start of the first product in the study.

Second, empirical studies report influences of several factory characteristics on manufacturing and total product ramp-up performance (Hayes and Clark 1986, Langowitz 1987, Clark and Fujimoto 1991, Kuhn et al. 2002). Although the facilities in our study represent a relatively standardized and homogeneous capacity pool, we consider four variables that may account for effects in ramp-up performance.

Plant age measures the time a plant has been in operation prior to the ramp-up start of each product. This measure serves as a proxy for the accumulated experience level of any given plant. *Plant ownership* is a dummy variable, for which 1 indicates in-house facilities and 0 means contracted facilities. In our sample, three of the nine facilities were owned by contract manufacturers, which were responsible for manufacturing up to a generic product level, before the units were shipped to in-house facilities for the final configuration and distribution. This variable might explain differences in the internal learning curve, problem-solving capability and supply logistics. *Plant location* captures differences in work force cultures and supply network structures. The measure is another dummy variable, divided into facilities located in Asia (China and Korea = 1) and facilities located in Europe (Germany, Hungary, Finland = 0).

The relationship between the complexity variables and manufacturing/total product ramp-up performance might also be influenced by the extent to which management adjusts sales plans and sales forecasts during the ramp-up preparation phase. In order to control for these effects, we introduce *sales forecast change* and *excess capacity*. The former is the ratio between the sales forecast quantity at the start of the ramp-up period and the sales forecast quantity 12 weeks before the start of this period. The latter is similar to the construct from organizational theory (Nohria and Gulati 1996): the capacity and availability of materials in excess of the necessary minimum to produce a needed level of output. Thus, we calculate excess capacity as 1 minus the ratio between the confirmed volume plan and the planned allocated capacity – both captured at the start of the ramp-up period and calculated for the entire ramp-up execution period.

Table 4. Summary of variables and definitions

Hardware complexity variables

common component count = all components in the product's bill of material list that are assembled onto the printed wiring board

product specific component count = total component count in the product as on a bill of materials parts list – *common component count*

parts coupling = number of signal networks across all electrical and electromechanical components in the product

$$product\,novelty = \frac{\text{material value of new physical components in the product}_{\text{average over period } T_{\text{RU\_EXE}}}}{\text{total material value of the product}_{\text{average over period } T_{\text{RU\_EXE}}}}$$

Software complexity variables

SW novelty = number of features in the product that have not yet been included in previous products or the existing software baseline

SW code size = source code size in terms of executable lines of code

SW error count = number of reported errors during the software acceptance/verification phase

Manufacturing and total product ramp-up performance variables

$$final\ yield\ = \frac{passed\ units_{\text{at test phase 1 over period } T_{\text{RU\_EXE}}}}{all\ tested\ units_{\text{at test phase 1 over period } T_{\text{RU\_EXE}}}} * \frac{passed\ units_{\text{at test phase 2 over period } T_{\text{RU\_EXE}}}}{all\ tested\ units_{\text{at test phase 2 over period } T_{\text{RU\_EXE}}}}$$

Note:

$$passed\ units_{\text{at test phase 2 over period } T_{\text{RU\_EXE}}} = actual\ production\,output$$

$$effective\ utilization = 1 - \frac{lost\ capacity_{\text{over period } T_{\text{RU\_EXE}}}}{planned\ allocated\ capacity_{\text{at } t_{\text{RU\_START}} \text{ over period } T_{\text{RU\_EXE}}}}$$

$$total\ product\ ramp-up\ performance = \frac{actuals\ invoiced_{\text{over period } T_{\text{RU\_EXE}}}}{confirmed\ volume\ plan_{\text{at } t_{\text{RU\_START}} \text{ over period } T_{\text{RU\_EXE}}}}$$

Control variables

linear trend = number of days between ramp-up start of each product versus ramp-up start of the first product in the study

plant age = number of years a manufacturing plant was in operation until the ramp-up start of each product

$$plant\ ownership = \begin{cases} 1 \text{ if in-house facility} \\ 0 \text{ otherwise} \end{cases}$$

$$plant\ location = \begin{cases} 1 \text{ in case of Asian plants (China, Korea)} \\ 0 \text{ in case of European plants (Germany, Hungary, Finland)} \end{cases}$$

$$sales\ forecast\ change = \frac{sales\ \ forecast\, quantity_{\text{at } t_{\text{RU\_START}} \text{ over period } T_{\text{RU\_EXE}}}}{sales\ \ forecast\, quantity_{\text{at } t_{\text{PREP\_START}} \text{ over period } T_{\text{RU\_EXE}}}}$$

$$excess\ capacity = 1 - \frac{confirmed\ volume\ plan_{\text{at } t_{\text{RU\_START}} \text{ over period } T_{\text{RU\_EXE}}}}{planned\ allocated\ capacity_{\text{at } t_{\text{RU\_START}} \text{ over period } T_{\text{RU\_EXE}}}}$$

2.3 Hypotheses

In the previous discussion (see also Figure 3), we note that the co-design of software and hardware is a central system characteristic of cell phones or embedded systems in general (Wolf 1994). For example, the integration of personal navigation in cell phones requires not only the development of a large share of dedicated software code but also the inclusion of additional components into the product (e.g., GPS receiver with discrete circuitry and antenna). However, there is a shift towards software-based implementations as most of the new innovations in cell phones are software-related (e.g., augmented reality, games, video processing, social networking clients), since hardware release cycles are more expensive and time consuming. Thus, hardware modifications and extensions often emerge as a side effect when new software features – for example a social networking client – demand more processor power, memory size, or connectivity speed. Consequently, higher levels of software complexity are counterproductive for preserving hardware integrity as they may increase hardware complexity in terms of component count, parts coupling, or product novelty. We accordingly state our first Hypothesis:

HYPOTHESIS 1. *Software complexity positively affects hardware complexity.*

As outlined above, embedded software represents a core integration activity for cell phone projects and most observers acknowledge the difficulty of ensuring the completion of software-intensive projects in budget and on time (Austin 2001, Lindstrom and Jeffries 2004). For example, manufacturing cannot be executed as planned if the required software or customer specific configuration files are missing, for instance due to delayed regulatory or customer approvals (e.g., from large operators). In addition, cell phone production entails complex automatic test systems to calibrate wireless protocols, power management, or to control the manufacturing process. New or complex software features or interfaces can cause these tests to fail, resulting in reduced manufacturing output. Hence, we formally state:

HYPOTHESIS 2. S*oftware complexity negatively affects manufacturing ramp-up performance.*

Decisions about the number of components to be incorporated into a design and decisions about how much novelty to impose on a new product also relate closely to several important issues for operations. Ambitious products provide a fundamental source of difficulty for manufacturing (Langowitz 1987, Kuhn et al. 2002, van der Merwe 2004, Keil et al. 2007). Since complex product designs make specific demands on factories and since factories have unique sets of skills that they can use to meet those demands, initial manufacturing ramp-up performance is a matter of accurate product–factory fit (Langowitz 1987). Typically, more complex products require more process steps and thus create more opportunities for process failure (Swink 1999). In addition, complex product design specifications frequently require more engineering change orders which may also affect performance in a negative way. Likewise, upstream supply operations face similar difficulties and affect manufacturing ramp-up performance via material supply shortages and mismatches (Almgren 2000) leading to our third Hypothesis.

HYPOTHESIS 3. *Hardware complexity negatively affects manufacturing ramp-up performance.*

Several studies have identified a relationship between product characteristics and total product ramp-up performance (Langowitz 1987, Almgren 2000, Kuhn et al. 2002, van der Merwe 2004, Schuh et al.

2005). Complex products – whether they involve hardware or software complexity – are less likely to accomplish customer acceptance because the lack of experience in the use of a new, complex product reduces the user's ability to describe its needs (Thomke and Bell 2001). This complicates project management as customers revise their requirements more often, request new customization options, or even find new errors after pretesting the new product. In addition, there is consensus that material problems (e.g., dimensional variations or delayed deliveries) and quality issues (visual defects or software variant difficulties) are more likely to occur in complex designs (Clark and Fujimoto 1991, Almgren 2000, Kuhn 2002). As a result, delivery commitments have to be lowered or shipments will lag behind planned schedules. Hence, we state:

HYPOTHESIS 4. *Software complexity negatively affects total product ramp-up performance.*

HYPOTHESIS 5. *Hardware complexity negatively affects total product ramp-up performance.*

Cell phones are manufactured with delayed customization (i.e., postponement), thus the final customization does not take place until real customer orders are known. As a result, manufacturing ramp-up performance represents how well the generic part of a cell phone is manufactured and how well aggregate production plans are met. Total product ramp-up performance instead measures how well the generic products can be converted into customer-specific cell phones that are subsequently distributed and invoiced. While these items are distinct in nature, previous research states a relationship between superior manufacturing performance and successful ramp-ups (Clark and Fujimoto 1991, Wildemann 2007). In other words, product availability is a pre-condition for product sales which leads us to our last Hypothesis.

HYPOTHESIS 6. *Manufacturing ramp-up performance positively affects total product ramp-up performance.*

2.4 Data and Methodology

The data for our study pertain to 46 products that were developed at R&D centers in four countries between 2005 and 2008 as already outlined in section 1.2.1. Our method of data collection was guided primarily by our conceptual model and employed multiple data sources, including project documentation systems, production databases, management information system reports, data archives and company reports. All operational definitions of the variables were additionally validated on the basis of interviews with several project managers and senior managers, as well as with a written questionnaire targeted toward the product ramp-up managers (refer to Appendix-D2). These data provided additional insights into the many qualitative disturbance issues during the ramp-up phase. In addition, we collected longitudinal data over the course of four projects, through the efforts of the author who is employed as a ramp-up manager by Nokia. Our unique database thus features highly reliable quantitative and qualitative information about the characteristics of each product; its development, production, and logistics process and the results of interviews and observations with key informants. Whenever possible, we triangulated the qualitative data with mandatory milestone review documents and expert opinions to confirm their accuracy and consistency. Table A-1 in the Appendix presents descriptive statistics and correlations for our variables. Correlations are generally as expected and moderate in magnitude. For confidentiality, we normalized the SW error count variable to have a mean equal to 1,000.

We use multiple linear regression models to test our Hypotheses. To enable comparison of effect sizes, we standardized all variables (mean = 0, variance = 1) before running the regression calculations. This is useful as our data is a mixture of different scales (e.g., component count uses pieces, linear trend uses days). Unstandardized results are provided in Appendix-A2-4. The assumptions of our multiple regression models were tested by several statistical methods. First, all data panels were screened for abnormal observations to avoid bias in the regression calculations. Next, predicted values were plotted against standardized residuals to show a random scattered pattern, supporting the assumption of linearity and homoscedasticity. For each regression, we calculated variance inflation factors to rule out multicollinearity problems. Resulting variance inflation factors (≤ 7) indicated no significant multicollinearity effects for any of the models (Hair et al. 2006). Also, normality of the error term is supported by the appropriate histograms and normal probability plots.

2.5 Results

The analysis was divided into three stages. First, we used multiple regression models to test the effects of software complexity variables (i.e., SW novelty, SW code size and SW error count) on each of the three variables of hardware complexity separately (Table 5). In the second stage of the analysis, we used multiple regression to test for Hypotheses 2 and 3 – the effect of complexity variables on the manufacturing ramp-up performance variables (i.e., final yield and effective utilization). In the final stage, we employed multiple regression (Table 7) to test the combined effect of the complexity and manufacturing ramp-up performance variables on total product ramp-up performance (Hypotheses 4-6). For brevity we only discuss the full models (including controls).

Table 5. Regression results (H1)

	Dependent variables			
	common component count	*product specific component count*	*parts coupling*	*product novelty*
Predictor variables				
SW novelty	0.205 (0.151)	0.123 (0.118)	0.020 (0.119)	0.734 *** (0.081)
SW code size	0.128 (0.142)	0.627 *** (0.110)	0.571 *** (0.111)	-0.006 (0.076)
SW error count	0.256 * (0.150)	0.190 (0.117)	0.351 *** (0.118)	0.278 *** (0.081)
R-Sq(adj)	11.50%	46.60%	45.40%	74.30%

Notes: N = 46, values in parentheses are standard errors, *** $p \leq .01$, ** $p \leq .05$, * $p \leq .10$, two-tailed tests.

The results of Table 5 largely support Hypothesis 1. Six out of twelve possible relationships show strong and significant positive effects of software complexity variables on hardware complexity variables. Each software complexity variable significantly relates to at least one hardware complexity variable. We also observe the strongest relationship between SW novelty and product novelty (β = 0.734). In general, increasing levels of software complexity are associated with higher levels of hardware complexity.

The results of Table 6 provide partial support for Hypotheses 2 and 3 in which we respectively state that increased software and hardware complexity are negatively associated with final yield and effective utilization. The results also suggest that hardware complexity acts as a mediator for the software complexity variables. In the case of final yield and effective utilization, the effect of nearly all software complexity variables is weakened by the presence of hardware complexity variables. In other words, hardware complexity – in particular product specific component count and parts coupling – is the mechanism by which software complexity affects final yield and effective utilization. We provide a more thorough discussion of this effect in the next chapter. Final yield and effective utilization are strongly dependent on product specific component count and parts coupling which are in turn determined by software complexity as a result of the prevailing embedded systems approach that we have discussed earlier.

The most comprehensive models (all variables included) demonstrate that product specific component count provides the strongest effect on final yield (β = -0.521) of all variables and a strong effect on effective utilization (β = -0.375). We also find a significantly negative effect of linear trend on final yield (β = 0.416), indicating that final yield of cell phone manufacturing seems to be a function of the number of product specific components and cumulated learning. This finding is plausible as product specific components increase the failure opportunities in production. For effective utilization, we observe parts coupling (β = -0.480) in addition to product specific component count (β = -0.375) to exert a strong and significant influence, revealing that manufacturing ramp-up performance in the form of good output increases while product specific component count and parts coupling are decreasing. Except for plant location (β = 0.332) that we discuss thoroughly in chapter 4, none of the other variables show a significant effect on final yield or effective utilization at the 0.10 level. Finally, the effects regarding product specific component count and parts coupling remain stable in all models. This supports the robustness of our results. The explained variance in both models is substantial (R^2 = 53% for final yield, R^2 = 54.4% for effective utilization) despite the reasonable number of significant variables.

Table 6. Regression results (H2 and H3)

	Dependent variables					
	final yield			*effective utilization*		
Predictor variables						
SW novelty	-0.355 ** (0.124)	-0.273 (0.214)	0.250 (0.272)	-0.209 (0.145)	-0.349 (0.213)	0.166 (0.268)
SW code size	-0.244 ** (0.116)	0.012 (0.174)	-0.185 (0.179)	-0.323 ** (0.136)	0.036 (0.173)	-0.046 (0.176)
SW error count	-0.360 ** (0.123)	-0.244 (0.149)	-0.147 (0.150)	-0.182 (0.145)	-0.041 (0.148)	-0.021 (0.147)
common component count		-0.144 (0.154)	-0.107 (0.162)		-0.218 (0.161)	-0.100 (0.160)
product specific component count		-0.359 ** (0.162)	-0.521 *** (0.163)		-0.298 * (0.154)	-0.375 ** (0.161)
parts coupling		-0.022 (0.194)	-0.114 (0.192)		-0.319 * (0.193)	-0.480 ** (0.189)
product novelty		-0.011 (0.230)	-0.304 (0.237)		0.320 0.229)	0.077 (0.234)
Control variables						
linear trend			0.416 * (0.220)			0.276 (0.217)
plant age			-0.287 (0.175)			0.050 (0.172)
plant location			0.167 (0.195)			0.332 * (0.192)
plant ownership			0.042 (0.150)			-0.156 (0.147)
sales forecast change			0.177 (0.127)			-0.160 (0.125)
R-Sq(adj)	40.4%	46.1%	53.0%	18.2%	46.4%	54.4%

Notes: N = 46, values in parentheses are standard errors, *** $p \leq .01$, ** $p \leq .05$, * $p \leq .10$, two-tailed tests.

Table 7 contains the results for total product ramp-up performance representing the findings for Hypotheses 4–6. In the first column, we regress only the complexity variables on total product ramp-up performance in order to test whether final yield or effective utilization – that we add in a next step – act as mediators. Our results do not indicate any mediation as most of the complexity variable effects become actually stronger in the presence of final yield and effective utilization as we show in column 2. The non-significant effects of the complexity variables in column 1 suggest that the manufacturing ramp-up performance variables – effective utilization in particular – blur the effect of the complexity variables on total product ramp-up performance. Regressing effective utilization on total product ramp-up performance already accounts for 31.7% of the variance in total product ramp-up performance. In addition, SW novelty and product novelty affect total product ramp-up performance in a different way compared to effective utilization as we will describe more thoroughly in the next chapter. Hence, the effect of the complexity variables can only be detected if we simultaneously control for the impact of effective utilization in our models.

Contrary to our expectation, SW novelty appears to have a positive effect on ramp-up performance. In the absence of the control variables, the effect is strong but not yet significant ($\beta = 0.373$). However, it becomes strong and significant ($\beta = 0.742$) in the full model. Hence, we do not find support for Hypothesis 4. One possible explanation is the unpredictable nature of the implementation and testing effort of novel software features that frequently results in late project schedule slips. Factories appear to benefit from the extra waiting time for the approved software release, as this enables them to build up semi-finished product buffers and, consequently, achieve higher performance levels during the subsequent ramp-up phase.

In addition, product novelty has a negative effect on total product ramp-up performance ($\beta = -0.498$) providing support for Hypothesis 5. New physical elements are more likely to cause material supply problems and product quality issues, which both result in total product ramp-up performance drops compared to proven ones. While the effect of final yield on total product ramp-up performance is not significant ($\beta = -0.149$), the results show a strong and significant positive effect of effective utilization on total product ramp-up performance ($\beta = 0.789$). Again, these mixed results provide partial support for Hypothesis 6 and yield some interesting insights. Advances in capacity management are rather likely to pay off during the ramp-up phase than investments in yield improvement activities.

Of the control variables, only sales forecast change ($\beta = 0.235$) and excess capacity ($\beta = 0.429$) have a significant positive relationship with ramp-up performance.

The effect of sales forecast change suggests that when the demand for a product increases – compared to the fixed production plan at t_{RU_START} – management will do anything in their span of control to boost output up to material or capacity limitations, which will in turn lead to higher performance levels. On the other hand, management will respond with a decrease in output if demand weakens (to avoid excess inventories) with the consequence that ramp-up performance will drop.

The effect of excess capacity suggests that higher levels of planned allocated capacity (compared to the confirmed volume plan) dampens the negative impact of ramp-up disturbances (e.g., equipment breakdowns, material quality problems, customer rejections) but with the downside of creating idle capacity under steady or weak demand.

Table 7. Regression results (H4-H6)

	Dependent variable		
	total product ramp-up performance		
Predictor variables			
SW novelty	0.083 (0.299)	0.373 (0.249)	0.742 ** (0.282)
SW code size	0.171 (0.243)	0.140 (0.193)	0.004 (0.185)
SW error count	0.186 (0.208)	0.202 (0.171)	0.044 (0.156)
common component count	-0.054 (0.216)	0.202 (0.180)	0.266 (0.171)
product specific component count	-0.047 (0.227)	0.119 (0.194)	-0.106 (0.200)
parts coupling	-0.338 (0.271)	-0.053 (0.223)	-0.317 (0.217)
product novelty	-0.243 (0.321)	-0.531 ** (0.262)	-0.498 * (0.253)
final yield		-0.084 (0.182)	-0.149 (0.181)
effective utilization		0.899 *** (0.182)	0.789 *** (0.178)
Control variables			
linear trend			0.317 (0.262)
plant age			-0.033 (0.192)
plant location			0.203 (0.216)
plant owenership			-0.217 (0.153)
sales forecast change			0.235 * (0.136)
excess capacity			0.429 *** (0.153)
R-Sq(adj)	0.0%	33.5%	52.3%

Notes: N = 46, values in parentheses are standard errors, *** $p \leq .01$, ** $p \leq .05$, * $p \leq .10$, two-tailed tests.

2.6 Discussion

The key objective of this chapter has been to investigate the effect of product complexity characteristics on manufacturing and total product ramp-up performance using operational data from the cell phone industry.

To begin with, the significant and directional coupling between software and hardware characteristics supports our view that most of the new innovations in cell phones are primarily enabled by software and by the way in which software and hardware designs are integrated throughout Nokia's product development process. As already pointed out in section 1.2, Nokia's product development approach is based on the premise that design activities are best divided into a number of sequential project stages separated by milestones reviews. After a requirements analysis, functionality is split into features that are implemented in software, in hardware or in a combination of both. In an iterative process, based on the fabrication of a series of prototypes, software/hardware integration is synchronized and feedback on whether the design meets customer requirements is gathered. As a new project proceeds through these successive prototype rounds, the design evolves in increasing levels of maturity, from early engineering samples to salable products that contain the final hardware. Finally, extensive testing and fine tuning activities take place in the course of which software releases are introduced in frequent intervals and tested on the final hardware. During that phase, product development managers focus mainly on software stability as most of the remaining errors arise from the realized software features or hardware problems that are corrected in software to save time and money (software release cycles are shorter and more flexible than hardware release cycles). This uniqueness of embedded systems and traditional cell phones stands in contrast to other products groups (e.g., personal computers, high-end smartphones), that may show decoupled architectures and platform structures in the software and hardware development.

A second important finding is that the novelty variables of both software and hardware complexity are the most influential drivers of total product ramp-up performance. Interestingly, software novelty appears to be positively associated with total product ramp-up performance. Our explanation for this finding is in line with studies that found a positive relationship between increased software newness and the determinants of software development time (Callahan and Moretton 2001, Griffin 1997). The ongoing growth in software content, it's coding and testing effort as well as the flexibility of software to quick-fix detected hardware errors make software schedules increasingly unpredictable and vulnerable to late schedule slips. Hence, several studies acknowledge the difficulties of ensuring software-intensive projects to be completed within budget and on time (Austin 2001, Lindstrom and Jeffries 2004). Rather than suffering from delayed software readiness (as a result of higher SW novelty), firms may profit from it by starting the production gradually – despite rising inventory levels of semi-finished products – until the approved software release can be used for the re-programming of these product buffers and starting the regular ramp-up. Since the re-programming step is straightforward, quick and does not occupy any regular ramp-up production resources, it allows for higher output levels during the initial ramp-up phase. The practical significance of this result is that firms need to make a trade-off between the gains in total product ramp-up performance that are enabled through gradual production ahead of the delayed ramp-up start and the negative consequences of missed schedule adherence and hence delayed deliveries.

In contrast, we find that greater product novelty has a negative effect on total product ramp-up performance. Apparently, novel product designs increase the number of uncertain issues that development teams, suppliers and even customers must cope with. Hence, they require more training/learning effort by production engineers and operators (in-house and at suppliers) as well as by customers to achieve total product ramp-up performance levels similar to those of less novel designs. In other words, the more novel the product, the more learning effort is needed and the slower is the increase in manufacturing performance during ramp-up (van der Merwe 2004). Furthermore, we find that ramp-ups with large levels of product novelty are particularly slow at the beginning, forcing the ramp-up steepness to rise disproportionately towards the end of the ramp-up execution period in order to achieve the planned output levels. Thus, effective utilization may still reach planned levels but final configuration and distribution activities suffer due to the timely shifted and compressed availability of products for the final configuration and distribution stage.

Another important finding of our results shows that manufacturing ramp-up performance has a strong impact on total product ramp-up performance. However, this effect is due to effective utilization and not due to final yield. The absence of a significant effect of final yield suggests that yield losses are compensated through repair activities and therefore have a negligible effect on the output. This is in line with our observations that repair resources are allocated to production lines on a need basis and most of these failures are easy to fix.

On the other hand the effect of effective utilization suggests that capacity losses apart from yield losses like unscheduled downtime, scheduled maintenance, setup changes and reduced speed are more disruptive in ramp-up environments. Since these losses cannot be absorbed by repair activities, subsequent final configuration and distribution activities may not proceed as planned, customer shipments are delayed and finally total product ramp-up performance decreases. More specifically, unscheduled downtime as the key contributor of effective utilization is the result of external (e.g., missing components or material) and internal (e.g., equipment downtime) factors.

For example, most of the external disturbances are related to the inability of suppliers to deliver the right material on time and in the required quantity. This frequently leads to line stops as buffer stocks are not available during the early ramp-up phase. Various reasons are described in the literature (e.g., Langowitz 1987, Terwiesch et al. 1999, Almgren 2000, Pfohl and Gareis 2000) but our results suggest that the key contributors to material issues are related to the number of components and their interactions (parts coupling). This is because material management is a complex process and the number of unique parts thereby drives complexity which in turn negatively affects performance (Fisher et al. 1999). It requires considerable resources to forecast and coordinate the timely arrival of the many parts that go into a cell phone product in the required quantity. This process remains error-prone and is likely to be exposed to more engineering changes the more components are involved.

With regard to capacity losses due to internal factors, our observations and survey results indicate that test system downtime is the most frequent source of disturbance during ramp-ups. That is because these systems are among the most complex appliances in the factory and require the highest level of product specific adaptation and maintenance to run smoothly. Products with many single components and complex interactions typically require a more complex test hardware because the increased number of couplings results in more test points on the printed circuit board which in turn have to be accessed by the test system. In most cases, precision mechanical needle adapters are used to connect these test points with the test system measurement devices. Unfortunately, these needle adapters are very prone to damage during the early production ramp-up phase and damaged test equipment does not just result in decreased yield levels. More seriously, damaged or serviced test equipment has a direct effect on effective utilization since the equipment is not available during the repair or maintenance activity. The practical significance of this result is that the careful management of product design, with an in-depth understanding of the effect that product specific component count and parts coupling have on test system robustness (i.e., effective utilization) instead of final yield, is highly relevant for ramp-up success.

Finally, the effect of our last control variable, excess capacity holds an important managerial implication. Recall that excess capacity represents the percentage difference between the planned allocated capacity and the confirmed volume plan. The former represents all of the materials and capacity that is reserved for the production of a particular product. Ramp-up teams use the input from sales teams that intend to sell the product to define this quantity. The latter represents the volume plan used by sales teams to confirm customer orders. Hence, the confirmed volume plan is a balance between material supply risks, production capacity risks, schedule risks and anticipated sales projections steered by management. Decisions, such as allowing for higher levels of excess capacity – given a certain level of planned allocated capacity – and being more restrictive with initial sales volumes, are therefore likely to improve total product ramp-up performance but at the expense of total output, cost, and thus profit. Finding the optimal level of excess capacity is linked to the managerial actions regarding incentives and rewards to product development teams. If management demands high levels of profits, it needs to design incentive systems that reward product development teams for achieved total product ramp-up performance but in relation to the chosen level of excess capacity.

This relationship is complex and deserves further research attention with particular focus on the strategic priority of the firm with regard to output dependability against overall profit.

2.7 Conclusions

We have developed a set of regression models that relate quantitative product complexity characteristics – represented by software and hardware complexity variables – and manufacturing ramp-up performance variables to total product ramp-up performance. With operational data from the cell phone industry, our models explain most of the variation in total product ramp-up performance. Beyond the growing importance of software characteristics in driving hardware complexity, we find that certain hardware characteristics (i.e., product specific component count and parts coupling) impact the performance of the manufacturing system in terms of final yield and effective utilization. Finally, we find that effective utilization together with the novelty aspects of both software and hardware complexity (i.e., SW novelty and product novelty) are the key determinants of total product ramp-up performance.

This chapter also highlights the importance of a novelty versus total product ramp-up performance trade-off and the relevance to distinguish between software and hardware novelty in order to properly deal with this trade-off. Because it is the main objective of the high-tech industry to achieve full-scale production and thereby time-to-volume targets, our study underscores the importance of the trade-off between implementing more product novelty (that may create surplus consumer attraction) and achieving ramp-up performance targets. Furthermore, advances in information and communication technologies will presumably lead to further growth in software novelty across products. Hence, effective software engineering with the focus on schedule adherence is becoming a central capability for launching new products quickly onto the market.

We contribute to the field of operations management by demonstrating the relevant product and manufacturing characteristics associated with ramp-up performance by offering a substantially enhanced and more detailed understanding of the ramp-up process and by validating the results of previous exploratory and qualitative studies. For managers, our findings underscore the importance of managing effective utilization instead of final yield and highlight the potential for firms to influence total product ramp-up performance through deliberate product design decisions. Another contribution is our application specific and quantitative definition of product complexity in the domain of cell phones. We are confident that our definition – which combines hardware and software characteristics – can be extended to other areas and industries. For example, products such as hi-fi systems, game consoles, cameras and flat screens share similar product characteristics with cell phones and even modern automobiles have some comparable properties.

Although we have attempted to build a comprehensive model with precise observations and argumentation based on existing literature, we also note some limitations. First, the relationships derived from the variables studied here capture only half of the overall variability in total product ramp-up performance. Additional factors may explain and contribute to total product ramp-up performance, such as product development lead times and late project schedule slips. Further research should identify and specify these factors in detail, particularly with regard to schedule performance. Also, the relationships obtained may not reflect the magnitude of their effects at certain firms. In particular, the magnitude of the effects of product complexity on total product ramp-up performance would be expected to be larger at firms that launch a smaller number of products per year but with progressive complexity upgrades.

Second, we identified excess capacity as a managerial decision variable that strongly relates to total product ramp-up performance. This raises the possibility to use this variable as managerial instrument to gauge performance against profit. Ideally, a newsvendor type model would guide management action to set the optimal level of excess capacity according to the strategic priority of the firm.

Finally, our conclusions are based on an analysis carried out within a single company; a wider analysis with different firms from within the consumer electronics industry would enhance our capability to generalize. Nevertheless, we believe our results are generalizable to the consumer electronics industry because our data (1) came from different geographical development centers with different cultural and managerial properties; (2) included a variety of customer groups, ranging from direct shipments to operator-exclusive agreements; and also (3) confirm existing models from other areas, such as the car industry.

Chapter 3

How does Development Lead Time affect Performance over the Ramp-up Lifecycle[2]

Abstract: *In the fast-paced world of consumer electronics, short development lead times and efficient product ramp-ups are invaluable. The sooner and faster a firm can ramp-up production of a new product, the faster it can start to earn revenues, profit from early market opportunities, establish technology standards and release scarce development resources to support new product development projects. Yet, many companies fail to meet their time-to-market and time-to-volume targets and the complex interrelationships between product characteristics, development lead time and ramp-up performance are partly unexplored. In response to these limitations, this chapter focuses on three research questions: (1) To what extent is manufacturing ramp-up performance determined by product development process (i.e., development lead time) and product characteristics (i.e., product complexity)? (2) How do these relationships change in the course of the ramp-up lifecycle? and (3) How can the results be explained? Our results contribute to the field of operations management in three ways. First, we offer a more comprehensive and enriched analysis of the drivers for development lead time and manufacturing ramp-up performance in the cell phone industry. Second, we demonstrate that late schedule slips – although disastrous for customer relations in which due dates are crucial – provide the opportunity to build up (semi-finished) product buffers which in turn increase the initial manufacturing ramp-up performance. Third, we show that it is important to take these effects into account in a jointly and lifecycle-dependent manner.*

[2] The results in this chapter have also been presented in Pufall et al. (2012b).

3.1 Introduction

The speed and efficiency with which new products are developed and introduced into large-volume production has an important influence on competitiveness in manufacturing (Hatch and Mowery 1998). Particularly in the field of consumer electronics where product lifecycles shrink, technology advances and competition intensifies, short development lead times and efficient ramp-ups are invaluable for several reasons. First, the faster a company can ramp-up production of a new product, the more quickly it can begin to earn significant revenues from the new product and recoup its development investments (Pisano and Wheelwright 1995). Secondly, fast ramp-ups enable firms to profit from early market opportunities, set technology standards and accumulate experience with volume production. Finally, scarce product development and manufacturing engineering resources can be released to support subsequent product development projects instead of solving production problems.

Prior research has identified time related variables and other factors as determinants of ramp-up performance as we show in Table 1. However, most of these studies have examined development lead time (time-to-market) or ramp-up performance (time-to-volume) separately, while their interrelationship has received only little attention (Terwiesch et al. 1999, Gerwin and Barrowman 2002).

In this chapter we enhance our initial model (Figure 3) that considers ramp-up performance as being dependent on product complexity with the inclusion of development lead time in order to address three research questions: (1) To what extent is manufacturing ramp-up performance determined by product development process (i.e., development lead time) and product characteristics (i.e., product complexity)? (2) How do these relationships change in the course of the ramp-up lifecycle? and (3) How can the results be explained? We take a confirmatory and exploratory approach in order to answer these research questions. First, we operationalize development lead time, product complexity and manufacturing ramp-up performance based on our enhanced conceptual framework (Figure 6), then we integrate them into a partial least squares (PLS) path model. Before we explore how these relationships change over time by modifying the time horizon of our dependent variables we are testing our fundamental Hypotheses. Finally, we contextualize both findings in order to provide holistic and quantitative insights into the combined and time dependent relationships.

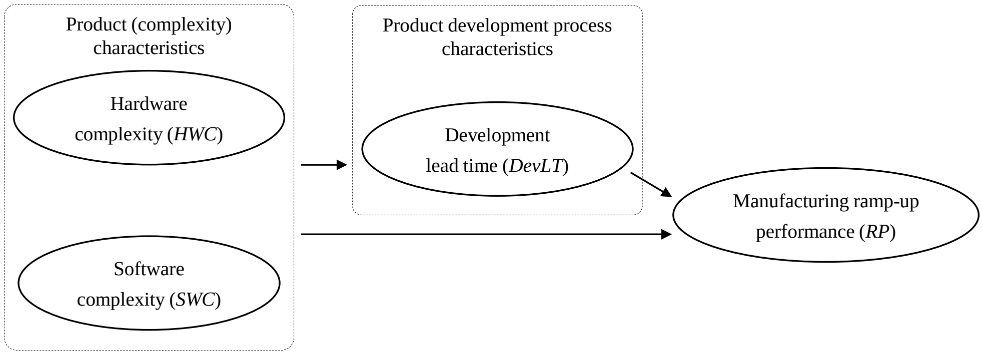


Figure 6. Conceptual framework

3.2 Measurement Model Operationalization

Although most of the variables that make up the measurement models in this section have already been introduced in chapter 2, we provide an additional short description for the sake of completeness and clarity. We begin with the operationalization of development lead time, an endogenous construct predicted by the product complexity framework that also acts as a predictor for manufacturing ramp-up performance. The logic derives from prior research that regards development lead time as a resource (Mallick and Schroeder 2005) and hence as a critical predictor for manufacturing ramp-up performance and also as a factor that is dependent on product complexity (Griffin 1993, Murmann 1994, Griffin 1997, Swink 2003).

3.2.1 Development Lead Time (DevLT)

Framed broadly, product development in the case firm involves five distinct activities: concept development; product planning; several cycles of design, build, integrate and test activities; product acceptance and production ramp-up. Due to general uncertainties at the start of the concept development for a particular product and due to the inherent dynamics in this phase (i.e., cancellations, redefinitions) our development lead time construct represents what Myers and Marquis (1969) call the problem-solving stage of development. This stage is separated into three key development phases. Each phase is framed by milestone reviews that denote business decision points in order to determine whether the previous development phase is completed against a set of clearly defined deliverables. Figure 7 outlines the different development phases with their respective milestones and outputs.

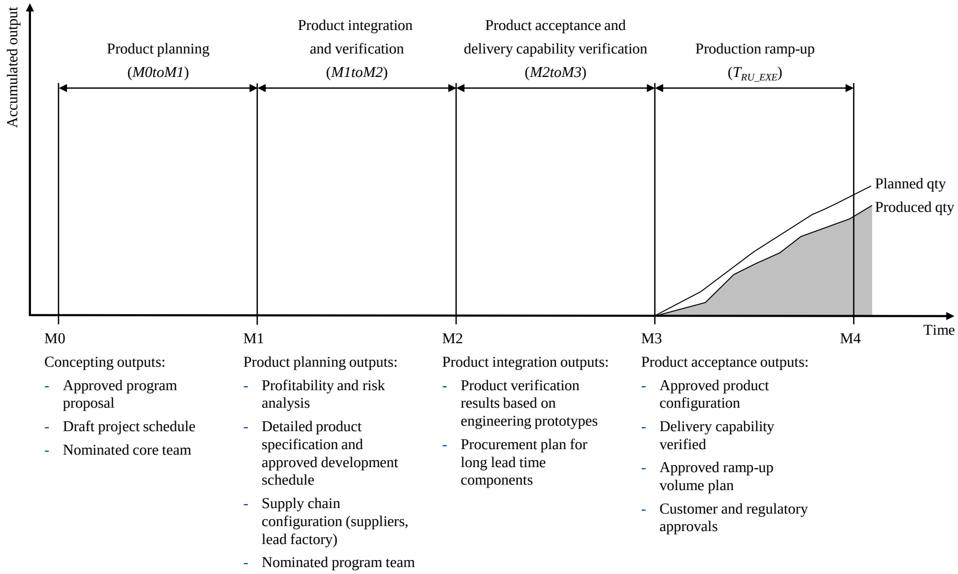


Figure 7. Definitions of major product development phases

M0toM1. This variable represents the elapsed time – measured in days – between the M0 milestone (i.e., the end of the concept development stage) and the start of the product integration and verification phase. It characterizes the efficiency of the product planning phase.

M1toM2. The product integration stage measured as the elapsed time in days between the M1 and M2 milestone involves several cycles of design, build, integrate and test activities. This is also known as a spiral product development process because the building and testing of prototype models has become such a rapid process that the design-build-test cycle can be repeated many times (Ulrich and Eppinger 2008).

M2toM3. During the product acceptance phase, engineering prototypes are assembled using the final assembly line and testing processes in the target factory in order to verify the performance of the production system (including supplier operations). These prototypes are also used to verify product reliability and to obtain all necessary regulatory and customer approvals. We measure this variable as the elapsed time in days between the M2 and M3 milestone.

With the approval of the M3 milestone, the production ramp-up finally starts. During this phase, the production output is determined by a push plan since detailed knowledge about sales demand does not exist at this stage. As soon as there is enough confidence to execute production according to sales forecasts, the ramp-up execution concludes. As the transition between ramp-up and mass-production is fluent, we consider different time horizons in our analysis as presented in section 3.5.4.

3.2.2 Hardware Complexity (HWC)

In compliance with our arguments from chapter 2, we consider hardware complexity in structural terms and hence as a property of the product (Rodriguez-Toro et al. 2004). Accordingly we apply Novak and Eppingers' (2001) definition that consists of three elements which serve as the indicators for our hardware complexity construct: (1) the number of product components to specify and produce, (2) the extent of interactions to manage between these components (parts coupling), and (3) the degree of product novelty.

Increased product functionality requires a larger number of components to be integrated into the architecture. Features like global positioning services (GPS), dual display functionality or hands-free stereo audio – to name just a few – cannot be implemented by means of software alone. However, the addition of extra components rises product complexity as a result of the more complex manufacturing process (Boothroyd et al. 1987), supply logistics (Fisher et al. 1999) or verification efforts (Novak and Eppinger 2001). While the definition of Ulrich (1995) states that a component can be any distinct region of the product, we divide our first indicator – the number of product components – into two parts to identify the relevant components in the context of manufacturing ramp-up performance: *common component count* and *product specific component count*.

Common component count comprises all components from the product's bill of material list like resistors, capacitors, transistors, connectors, shields and integrated circuits, which are assembled onto the printed wiring board. These components are freely available on the market and hence also used in other products from the case company or competitors. *Product specific component count* refers to components in the bill of materials list that are specifically developed for the use in a dedicated product. Hence, the options to use these components in other products or industries are very limited. Examples are plastic covers, antenna elements, stickers, foams, gaskets, displays and cables.

Please note that our definition does not include any sub-components that are inseparably embedded in advanced components (i.e., optical lenses in camera modules or glass layers in display units) as these components are not under managerial control or technically observable.

The second indicator of our hardware complexity construct is *parts coupling*. According to Novak and Eppinger (2001), parts coupling increases complexity because an increased number of interconnected parts within a system results in additional development risks, verification efforts and side effects. In other words: the more complex the interdependencies are, the greater is the added complexity (Williams 1999). In our operationalization of parts coupling, we measure the number of signal networks across all electrical and electromechanical components (i.e., components that carry any electrical functionality and account for around 70% of all components) within a product. R&D teams have confirmed that the reliable integration of components does not only require expert knowledge regarding the components themselves but also firm understanding of their simultaneous interactions. This definition acknowledges the fact that development teams must understand and integrate arrangements of interlinked signal networks – a task that is much more challenging than the simple understanding of component pairs (i.e., individual point-to-point connections).

The third indicator of our hardware complexity construct, *product novelty* describes how much of the product must be redesigned compared to previous products. It can either be conceptualized as the percentage of new designs comprised in the product (Swink 1999) or as the degree of similarity between a certain product and other members of its product family (Coughlan 1992). Our operationalization enriches these existing concepts by measuring the percentage material value within a product that is new to the responsible development center. Products may exhibit unique characteristics depending on whether we observe them at the overall final assembly level or as individual parts and subassemblies (Ulrich 1995). Since most of the components in our study are only observable on the first layer of abstraction (e.g., cameras, displays, processors, etc.) we consider them on a macro level. In this case, any definition based on the simple percentage of new parts would regard the contribution of each component to novelty as equal. However, the integration and testing effort as well as the supply risk during ramp-up for complex cameras, displays or processors is not comparable with the risks and efforts related to simple screws, foams or stickers.

3.2.3 Software Complexity (SWC)

The increasingly dominant role of software in modern consumer electronics products and its impact on product complexity, development schedules and budgets (Rauscher and Smith 1995, Blackburn et al. 1996) underlines the necessity to treat software complexity as a separate construct within our product complexity framework. Because software complexity is multidimensional in nature (Banker et al. 1998, Zuse 1991), several complexity measures have been proposed. Examples are McCabe's (1976) cyclomatic complexity, Wood's (1986) component/coordination/dynamic dimensions and Halstead's (1977) effort metric. Previous research, however, has found that these measures only vary on a small number of orthogonal dimensions (Banker et al. 1993, Munson and Koshgoftaar 1991) and that they incorporate common properties (Weyuker 1988). We apply a combination of indirect measures – calculated from the design specifications – and direct measures – calculated from the program code (Sunohara et al. 1981). Consistent with our approach to describe hardware complexity, we define software complexity as (1) the number of executable lines of code = SW code size, (2) the degree of software newness = SW newness, and (2) the number of software errors = SW error count. These measures refer only to the operating and application software modules that are under direct control of the firm (i.e., in-house developments). We exclude any software modules that are embedded in advanced components like displays or cameras (e.g., embedded driver software) and optional third-party applications that are not mandatory for the product launch. Thus we focus on the core elements of product software that the company has to provide timely, error free and in compliance with regulatory requirements.

SW code size. According to Huang (1998) the size of a program is one of many factors affecting its complexity. Lines of code measures have been widely discussed in the literature on embedded systems (Broy et al. 2007, Lee 2000) due to the importance of SW code size on system performance and costly memory size decisions. Within this study we measure SW code size as the number of executable lines of code. All products in our sample are based on identical engineering tools and programming languages (i.e., a proprietary language for lower-level signaling functions and C/C++ for higher-level code). Thus, the number of executable lines of code can be counted in a consistent manner and is hence unbiased within the sample (Krishnan et al. 2000).

SW novelty. The software engineering literature argues that adding more features or increasing the newness of a software product usually increases its complexity (Zuse 1991, Krishnan and Zhu 2006, Laird and Brennan 2006). This is plausible as new software features may have lower design integrity and quality – all else being equal – than existing software code that has already been tested and debugged across existing products. Hence, we operationalize SW novelty as the number of new software features in a product that have not been included in previous products or in the existing software baseline. A new feature is characterized by the necessity to either develop/implement new software components or to modify existing components instead of reusing existing software components.

SW error count. Both, SW newness and SW code size do not sufficiently account for differences in the individual product configuration as these measures regard software components as having in-built complexities that are static and independent of their context. For example, products that contain a decent amount of SW newness and consist of a trivial code size may still require a disproportionate amount of development effort since interactions and side effects in a particular product configuration may result in a large number of errors. Because errors are strongly related to complex programs (Basili and Perricone 1984) and defects are strongly associated with software complexity (Harter and Slaughter 2003, Kafura and Reddy 1987), we include a measure of SW error count (identified during the product integration and acceptance phase while the product passes through a series of standardized acceptance tests) as our third indicator of software complexity.

3.2.4 Manufacturing Ramp-up Performance (RP)

Based on the existing ramp-up literature there seems to be a broad consensus to measure ramp-up performance in terms of output against time or plan (Langowitz 1988, Clark and Fujimoto 1991, Terwiesch 1999, Almgren 2000, Kuhn et al. 2002, Merwe 2004, Schuh 2005). For other measures like quality, time, yield or cost there seems to be little – if any – common norm. This is partly due to the fact that each study measured ramp-up performance according to its own specific situation, characterized by different competitive priorities. For example, unit cost might be a negligible performance measure in cell phone projects as the profits gained due to successful early sales (enabled by reliable output against plan) – customers are most willing to pay premium prices during the early product lifecycle – typically outweigh all other cost related drivers. Also, it is economically unwise to focus on absolute ramp-up speed or time because quality and other cost drivers can accumulate to levels that sustainably affect the overall company competitiveness (Voigt and Thiell 2005). Hence, our second endogenous construct represents output against plan, frequently cited as effective utilization (Konopka 1995, Matsuo et al. 1997, Terwiesch et al. 1999). We measure it as the ratio between produced quantity during the ramp-up period and planned quantity at the beginning of the ramp-up period.

3.2.5 Control Variables

We control for several other variables to strengthen non-spuriousness between the complexity constructs, development lead time and manufacturing ramp-up performance. Note that we do not control for in-house manufacturing depth since our sample does not show any substantial variance regarding this aspect.

First, we control for learning effects with the supposition that a firm gains development experience and hence the performance regarding development lead time and ramp-up will increase over time. We label this variable *linear trend* and measure it as the number of days elapsed between the ramp-up start of each new product versus the ramp-up start of the first product in the study.

Second, we control for differences in the planning approach and the number of design-build-test cycles, which may dictate development lead time to a certain extent. We label this variable *planned development lead time*. It represents the number of workdays from concept approval to ramp-up start, estimated at the time of concept approval.

Third, we control for whether the project experienced any delay during the product acceptance phase. We measure *slip* as the number of workdays between the estimated (provided at the M2 milestone) and the actual ramp-up start. Compared to projects that are able to ramp-up on time, delayed projects are more likely to face problems during the ramp-up phase that are related to the cause of the original delay. However, project delays can also allow program teams and suppliers to utilize the gained time productively and hence to be more successful regarding manufacturing ramp-up performance.

Forth, we include a sequence of seven dummy variables that are tested one after the other in order to control for plant specific effects. Although the plants in our study represent a standardized and homogeneous capacity pool, empirical studies have reported that factory characteristics may influence production performance (Hayes and Clark 1986, Langowitz 1987, Clark and Fujimoto 1991, Kuhn et al. 2002). Each of these variables is coded as one for the focus factory, zero otherwise and labeled as *factory ID1…7*.

Fifth, we control for two additional plant specific effects. In order to measure the level of experience in any given plant we include a variable labeled *plant age*. This variable represents how long a plant has been in operation prior to the ramp-up start of each product.

Furthermore, we capture differences in work force culture and supply network structure that originate from differences in the physical location of each factory with regard to their main supply base that is located in China. The dummy variable *plant location* is coded as one if the plant in question is located in Asia (China and Korea) and zero if it is located in Europe (Germany, Hungary, Finland).

Sixth, we add a measure for *sales forecast change* in order to control for changes in the sales volume forecast during the ramp-up execution phase. We use the relative change in the sales forecast between the beginning and end of the ramp-up execution period to remove the effects of sales fluctuation on production execution. For example, there might be low demand for a product compared to the original production plans created at the start of ramp-up. The factories will thus respond with reductions in output, which will in turn lead to low effective utilization levels although production performance itself is good.

Finally, we control for *production technology novelty*, a dummy variable that is coded as one if considerable resource investments (e.g., equipment, engineering labor) are needed *and* no contingency plans exist, zero otherwise. We believe that the combination of resource investments and the absence of a back-up plan are of particular interest. We expect that production technology novelty has a negative impact on effective utilization as new technologies entail significant fine-tuning and testing and may – relative to “proven” technologies – expose a firm to risks of failure in terms of durability and reliability (Clark and Fujimoto 1991). Examples that belong to this group are decoration technologies (e.g., high-gloss paint effects), manufacturing process technologies (e.g., RoHS implementation) or production testing technologies (e.g., WCDMA testing). These technologies require considerable resource investments while prevailing technologies cannot be used as backup solutions. Table 8 summarizes the various indicators of the constructs described in this section, as well as their definitions and formulas.

Table 8. Summary of constructs, indicators, and definitions

Development lead time (*DevLT*)

M0toM1 = elapsed time in days between the M0 and M1 milestone (i.e., the product planning phase)

M1toM2 = elapsed time in days between the M1 and M2 milestone (i.e., the product integration and verification phase)

M2toM3 = elapsed time in days between the M2 and M3 milestone (i.e., the product acceptance and delivery capability verification phase)

Hardware complexity (*HWC*)

common component count = all components in the product's bill of material list that are assembled onto the printed wiring board

product specific component count = total component count – *common component count*

parts coupling = number of signal networks across all electrical and electromechanical components in the product

$$product\,novelty = \frac{\text{material value of new physical components in the product}_{\text{average over period } T_{\text{RU\_EXE}}}}{\text{total material value of the product}_{\text{average over period } T_{\text{RU\_EXE}}}}$$

Software complexity (*SWC*)

SW code size = source code size in terms of executable lines of code

SW novelty = number of features in the product that have not yet been included in previous products or in the existing software baseline

SW error count = number of reported errors during the product integration/acceptance phase

Manufacturing ramp-up performance (*RP*)

$$effective\ utilization = \frac{actual\ production\,output_{\text{over period } T_{\text{RU\_EXE}}}}{planned\ \ production\,output_{\text{at M3over period } T_{\text{RU\_EXE}}}}$$

Control variables

linear trend = time in days between the ramp-up start of each new product versus the ramp-up start of the first product in the study

planned development lead time = time in days between concept approval and ramp-up start, estimated at concept approval

slip = elapsed time in days between the estimated (provided at the M2 milestone) and the actual ramp-up start. Please note that this indicator becomes positive if the actual ramp-up start is ahead of the planned date.

$$factory\ ID1\ldots7 = \begin{cases} 1 \text{ for the respective factory} \\ 0 \text{ otherwise} \end{cases}$$

plant age = indicating how many years a plant was in operation before the ramp-up start of each product

$$plant\ location = \begin{cases} 1 \text{ in case of Asian factories (China, Korea)} \\ 0 \text{ in case of European factories (Germany, Hungary, Finland)} \end{cases}$$

$$sales\ forecast\ change = \frac{sales\ forecast\ quantity_{\text{at M3 over period } T_{\text{RU\_EXE}}}}{sales\ forecast\ quantity_{\text{12 weeks before M3 over period } T_{\text{RU\_EXE}}}}$$

$$production\ technology\ novelty = \begin{cases} 1 \text{ considerable resource investments needed and no contingency plans exist} \\ 0 \text{ otherwise} \end{cases}$$

3.3 Structural Model and Hypotheses

Figure 8 illustrates our PLS path model including the previously operationalized constructs and the hypothesized structural relationships between the constructs.

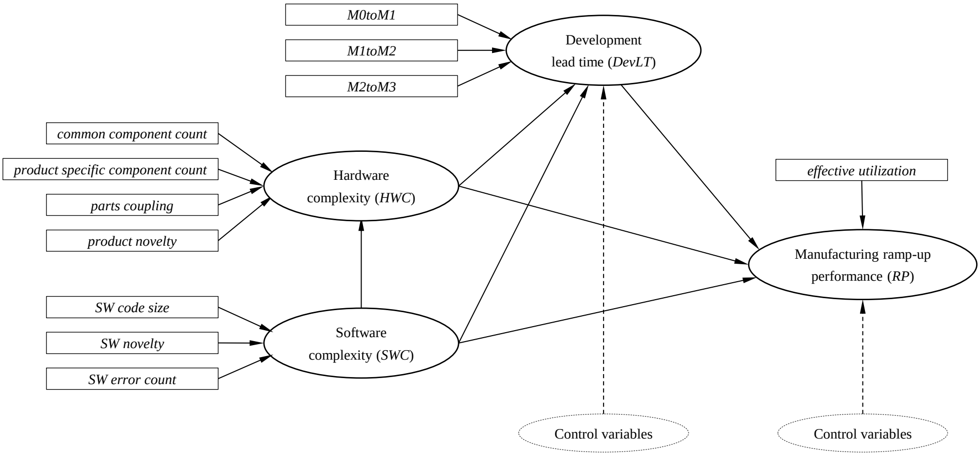


Figure 8. The PLS path model

All embedded systems and cell phones in particular are unique because they demonstrate a hardware-software co-design problem – hardware and software have to be designed together in order to make sure that the implementation does not only function properly but also meets all goals regarding performance, cost, and reliability (Wolf 1994). A new design is typically started with the creation of a requirements specification that includes all functional requirements – in other words the specific behavior of the system and nonfunctional requirements, including operability, certification, and cost. In a next step, an initial architecture is proposed including functions that are either assigned to be directly implemented into the hardware or into the software running on the hardware. Traditionally, hardware development dominated system development because of longer lead times and logistical dependencies on external suppliers. Consequently, software development started when hardware development was already at a stage where changes would be extensive (Graaf et al. 2003). However, hardware release cycles are expensive and inflexible, so software based implementations have become a more common approach (Lee 2000, Graaf 2003, Sangiovanni-Vincentelli and Martin 2001). Additionally, most of the new innovations in cell phone products originate from software features like social networking clients, augmented reality, picture processing or games. Hence, the hardware configuration (e.g., processor speed, memory size, interfaces, camera pixel size) is determined by a rising amount of functional requirements that are implemented into the software. We therefore hypothesize the following:

HYPOTHESIS 1. *Software complexity (SWC) positively affects hardware complexity (HWC).*

Several studies in the literature on operations management, product development and software engineering have found a positive association between product complexity and development lead time (Clark and Fujimoto 1989, Griffin 1993, Callahan and Moretton 2001, Swink 2003). According to Swink (2003) this is likely to be a result of the growing size and uncertainty of the design task if increasing numbers of interacting components are involved. Completing such a design task requires several design-build-test iterations or problem solving cycles until the requirements are met, regardless whether they are related to software or hardware. As a result, lead time in a program will be affected by the length of each problem solving cycle, the number of iterations and patterns of informational linkage among the cycles (Clark and Fujimoto 1989). Although these arguments are valid for both complexity dimensions, hardware complexity may dominate as a result of the longer development lead times for components. On the other hand, software can also play a dominate role, due to the steady shift of functionality from hardware to software (Lee 2000, Graaf et al. 2003, Sangiovanni-Vincentelli and Martin 2001) and due to the tendency to fix hardware errors via software solutions (Rauscher and Smith 1995, Graaf et al. 2003). These arguments lead to the following two Hypotheses:

HYPOTHESIS 2. *Software complexity (SWC) positively affects development lead times (DevLT).*

HYPOTHESIS 3. *Hardware complexity (HWC) positively affects development lead times (DevLT).*

Because the replication process of software in embedded systems is simple (i.e., it typically consists of a simple programming step during production) we could conclude that manufacturing ramp-up performance can no longer be adversely affected by the level of software complexity after the software has been released for production. However, the manufacturing environment for cell phones is characterized by complex multistage assembly lines and includes several test phases. Potential drivers for manufacturing ramp-up performance include the tight interdependence between these automatic test systems and the product software as well as the on-time availability of approved software variants. Addressing these issues one at a time, we note that complex product software necessarily increases the test software algorithms (Schaub and Kelly 2004). Firstly, due to the increased number of test steps in order to calibrate wireless protocols or other components and secondly, due to the interactions between the product software and the test system that also have to be managed. Both conditions may lead to decreased yield and hence to decreased production output. In addition, production output is dependent on the scheduled readiness of customer specific software variants. Complex software, however, makes it more likely that customers revise requirements (Thomke and Bell 2001), find new errors after pretesting or request changes in the customization options. Manufacturers are often forced to adapt or lower production plans due to these circumstances. Therefore we state the following:

HYPOTHESIS 4. *Software complexity (SWC) negatively affects manufacturing ramp-up performance (RP).*

A rich stream of studies has demonstrated that product complexity in terms of physical product characteristics is negatively associated with manufacturing ramp-up performance (Langowitz 1987, Swink 1999, Terwiesch et al. 1999, Vandevelde and Van Dierdonck 2003, Keil et al. 2007). Higher levels of complexity and uncertainty regarding product and technology will cause more difficulties in the attempt to realize a smooth production start-up (Vandevelde and van Dierdonck 2003). Complex products may push the limits of manufacturing process capabilities and require more process steps, thus opening up more opportunities for process failure (Swink 1999). At the same time extra learning efforts regarding manufacturing engineering and improved operator training are required to achieve the desired performance level. Engineering changes may appear more frequently and cause the most disruptive effects at the very beginning of the manufacturing start (Coughlan 1992). Similar challenges are also likely to occur at upstream partners (i.e., suppliers), thereby disturbing manufacturing ramp-up performance due to problems with material supply and quality (Almgren 2000). For these reasons we state the following Hypothesis:

HYPOTHESIS 5. *Hardware complexity (HWC) negatively affects manufacturing ramp-up performance (RP).*

Cell phone projects involve different organizational functions that are concurrently conducting development tasks in order to minimize development lead time. However, prior research has been inconclusive regarding the actual effectiveness of process concurrency or its accelerating effect on operational outcomes (Tatikonda and Montoya-Weiss 2001). For example, Wheelwright and Clark (1992) found that concurrency is beneficial to operational outcomes other than lead time because more information can be shared between organizational functions. Improved understanding of requirements and limitations enables cooperative problem solving activities as well as earlier anticipation of project challenges. On the contrary, concurrency may lead to increased risk if the downstream function is forced to make decisions (such as orders of product specific manufacturing equipment) before final fixed data is available from the upstream function. This can delay production line approvals and cause rework — ultimately leading to missed output targets. Furthermore, the longer the time available to study user needs and develop and test alternative concepts for technical feasibility, the greater is the likelihood that a better solution will be found (Mallick and Schroeder 2005). Also, extended development lead times may be the result of additional problem solving cycles or pilot production rounds that improve product and production process maturity levels and hence facilitate a smooth production ramp-up. We posit the latter effect and conjecture our last Hypothesis:

HYPOTHESIS 6. *Development lead time (DevLT) positively affects manufacturing ramp-up performance (RP).*

Please note that we explore the effects that are described in hypotheses 4, 5 and 6 under different time horizons of the ramp-up execution period in the results section. For brevity we do not discuss the related Hypotheses.

3.4 Methodology

In order to test our Hypotheses, we employ a variance based structural equation modeling approach known as PLS path modeling. Compared to covariance based structural equation modeling approaches (e.g., LISREL), PLS is particularly well suited for studies using operational data and if the primary research objective is the maximization of explained variance in the endogenous constructs (i.e., prediction) instead of achieving model "fit". Operational data frequently violates the requirement of multivariate normality and sample sizes are limited by the number of real life cases. PLS, however, does not make any assumptions of the underlying distribution and provides stable estimates even if the ratio of observations to parameters is small (Wold 1982, Fornell and Bookstein 1982, Chin 1998, Hair et al. 2011). In addition, PLS allows for the simple configuration of formative measurement models. In accordance with the decision rules by Jarvis et al. (2003) and Petter et al. (2006) our indicator operationalization advocates a formative coding scheme as we point out in Table 9.

Table 9. Measurement model specification criteria

Decision rules according to Jarvis et al. (2003)	Comments
1. Direction of causality from construct to measure implied by the conceptual definition • Are the indicators (items) (a) defining characteristics or (b) manifestations of the construct? • Would changes in the indicators/items cause changes in the construct or not? • Would changes in the construct cause changes in the indicators?	Our indicators are defining characteristics of the constructs. Increasing the value of any indicator will directly translate into a higher or lower score for the overall construct scale, regardless of the value of other indicators and thus supporting a formative coding scheme.
2. Interchangeability of the indicators/items • Should the indicators have the same or similar content? Do the indicators share a common theme? • Would dropping one of the indicators alter the conceptual domain of the construct?	In line with the formative decision rules (Jarvis et al. 2003) our indicators are not interchangeable (e.g., each indicator in the hardware complexity construct captures a specific aspect of hardware complexity). Hence, dropping one of the indicators would seriously alter the conceptual domain of the construct.
3. Covariation among the indicators • Should a change in one of the indicators be associated with changes in the other indicators?	These criteria are not necessary for formative indicators (Jarvis et al. 2003).
4. Nomological net of the construct indicators • Are the indicators/items expected to have the same antecedents and consequences?	Formative indicators are not expected to have the same antecedents and consequences and the nomological net may differ (Jarvis et al. 2003).

The application of a formative measurement model has methodological implications. The concepts of internal consistency, reliability and convergent validity are not meaningful if formative indicators are involved (Hair et al. 2011). Hence, we base our formative indicators on theoretical rationale as outlined in section 3.2 and focus on the pure operational aspects of product complexity, development lead time and manufacturing ramp-up performance. This allows for conceptually rigorous and complete definitions supported by statistical criteria. Before we applied the algorithm we standardized our data (mean = 0, variance = 1) in order to support the interpretation of the path coefficients. Although not a precondition in PLS, data standardization is recommended if the variables are measured with different scales as in our case.

During the modeling process we were primarily guided by our conceptual framework and by our research objective to make predictions for real life cases (i.e., the maximization of explained variance in the endogenous constructs). Hence, we started with a model that was based on our conceptual framework which consists of four key constructs (SWC, HWC, DevLT, RP). In a next step, we subsequently added one control variable at a time (except for the factory ID variables) in different combinations. We only included variables in our model that demonstrated a significant effect (i.e., we dropped control variables that were non-significant or did not substantially alter the effects of the conceptually relevant variables). Afterwards, we successively included the individual factory ID variables in order to assess potential factory specific effects. In response to the results of this analysis, we decided to include plant location as an additional control variable. This configuration – that we refer to as M10 – turned out to be the most conclusive model according to our conceptual reasoning and offered the highest R^2 value regarding development lead time and manufacturing ramp-up performance. In a final step, we used the M10 model to assess the effects of different time horizons in manufacturing ramp-up performance and to estimate interaction effects between software and hardware complexity constructs.

3.4.2 Data Collection

Since most of the variables have already been introduced and operationalized in chapter 2, we only provide a short description at this point for the sake of completeness and with a focus on the new data sources.

The data for calculating the product development lead time indicators are taken from a project management reporting tool that records all planned and actual milestone dates throughout the project lifetime. Programs can only move to the next development phase and update the milestone dates if certain, well defined criteria are met and the respective milestone review is approved by the steering group. This property allows us to precisely calculate the duration of different development phases and other timing related variables (linear trend, planned development lead time, slip).

The data for our hardware complexity indicators – specifically common component count and product specific component count – were taken from the product data management system that is used for managing the bill of materials list. Our product novelty indicator was calculated with the help of the product specification documentation and the sourcing parts lists. The first tool provides an overview of the novelty/re-use status of each component while the second provides the material prices. The parts coupling indicator originates from the electronic design automation (EDA) tool.

The software related indicators were extracted from the compiler log files (SW code size), the requirements management system (SW novelty) and the error management databases (SW error count). Nokia products generally follow a highly disciplined and standardized software development and verification process that creates reliable and consistent data regarding the aforementioned software characteristics.

The variables regarding effective utilization and sales forecast change were calculated using data from a management information system report that contains sales forecasts, production plans and actuals on a monthly time scale. As a response to the short-term planning cycle of Nokia that spans a timeframe of 12 weeks we decided to peg our ramp-up execution period $T_{\text{RU\_EXE}}$ to this time horizon in the initial model which we relax in section 3.5.4. During this period most resources are considered to be fixed due to equipment and material procurement lead time limitations.

Finally, we enhanced our data with interviews, a written questionnaire that was completed by each ramp-up manager and milestone review documentation (refer to section 1.2.1). Using these sources we were able to gain additional insights into the qualitative issues that appear during each ramp-up and to gather data in order to operationalize our production technology novelty indicator. Descriptive statistics for our data and their correlations are presented in the Appendix-B1. All variables were screened for abnormal observations to avoid outlier bias in the PLS calculations. Due to confidentiality reasons the variable SW error count is normalized to have a mean equal to 1000.

3.5 Results

Following the structural equation modeling logic, the assessment of a PLS model follows a two-step approach that involves separate assessments of the measurement model and the structural model (Hair et al. 2006, Hair et al. 2011). All parameters within the model were estimated using smartPLS (Ringle et al. 2005) and XLSTAT version 2011.2.01. Additional statistics were calculated with Minitab version 16.1.1.

3.5.1 Validation of the Measurement Models

Formative measurement models are examined based on their indicator weights, their significance, their loadings and the degree of multicollinearity (Chin 1998, Tenenhaus et al. 2005, Hair et al. 2011). Significance levels were estimated by means of a *t*-statistic that is generated by a bootstrapping technique (based on 500 resamples). Additionally, we evaluated significance levels by reviewing bias and percentile ranges of the bootstrap output. We also used the conservative “construct level sign change” option (initial weight setting = 1.0, abort criterion = 1.0E-5) after checking the individual bootstrap results and applied two tail tests although the direction of our Hypotheses would allow for single tail tests. We calculated the variance inflation factor (VIF) for the assessment of multicollinearity. As the highest VIF in our measurement model turned out to be around two, multicollinearity is not likely to distort the estimates as a result of excess redundancy. In the context of PLS, the critical cut-off value for VIF is 5 (Hair et al. 2011).

Table 10 presents the results of our most conclusive measurement model (M10). Other measurement models that are part of the structural model variants that will be discussed in the next section are only provided in the Appendix-B2 since their difference is negligible. All formative indicators have strong and significant weights – with the exception of common component count – and there is no co-occurrence of negative and positive indicator weights in the same construct. Note that single-indicator constructs always appear significant (as used for the control variables and manufacturing ramp-up performance). This suggests that common component count does not provide additional explanatory power beyond the other indicators within the hardware complexity construct although it still represents an important aspect (the loading or bivariate correlation is substantial and significant). In other words, common component count is *absolutely* important but not *relatively* (Cenfetelli and Bassellier 2009). Its theoretical relevance, however, is justified as there are only few overlaps with the other indicators leading us to keep the indicator in the model. The novelty indicators in particular (product novelty and SW novelty) deserve closer attention. Their relative contribution to the complexity constructs is disproportionally high, emphasizing the importance of novelty as a key characteristic of complexity that can be used to predict development lead time and manufacturing ramp-up performance. In summary, our measurement model is characterized by robust and significant indicators that capture the domain of our constructs. This provides a strong foundation for construct validity.

Table 10. Measurement model results

	M10 (final model)			
	Path weight	*t*-value	Loading	VIF
Development lead time (*DevLT*)				
M0toM1	0.62 ***	5.73	0.76	1.05
M1toM2	0.75 ***	3.60	0.59	1.42
M2toM3	0.53 ***	2.79	0.16	1.37
Hardware complexity (*HWC*)				
common component count	0.07	0.56	0.45	1.65
product specific component count	0.28 **	2.18	0.63	1.53
parts coupling	0.38 **	2.29	0.68	2.14
product novelty	0.71 ***	4.76	0.84	1.09
Software complexity (*SWC*)				
SW novelty	0.54 ***	3.85	0.77	1.16
SW code size	0.40 ***	3.22	0.52	1.02
SW error count	0.51 ***	5.18	0.74	1.15
Ramp-up performance (*RP*)				
effective utilization	1.00	--	1.00	1.00

Notes: N = 46, *** p ≤ .01, ** p ≤ .05, * p ≤ .10, two-tailed tests based on 500 bootstrap resamples.

3.5.2 Validation of the Structural Models

The primary evaluation criteria for the structural model are the R^2 measures (=predictiveness) and the level and significance of the path coefficients (Chin 1998, Tenenhaus et al. 2005, Hair et al. 2011). Goodness of fit (GoF) indices or blindfolding procedures (Q^2) are only applied in the presence of reflective measurement models as they are based on the portion of explained variance in the indicators (see Stone 1974, Geisser 1977, Tenenhaus et al. 2005, Hair et al. 2011). All structural model parameters are estimated with the path-weighting scheme (for a discussion of weighting schemes, see Chin 1998, Tenenhaus et al. 2005). Despite the slightly increased VIF value of SWC → RP we discovered no inconsistency in the results during our multicollinearity assessment. With this assessment we tested additional models by removing one complexity construct at a time. Table 11 reports the results of our Hypothesis tests with regard to our most conclusive model (M10).

Table 11. Structural model results

	M10 (final model)			
	Path weight	*t*-value	Loading	VIF
Structural model (path coefficients)				
Direct effects				
SWC --> HWC	0.89 ***	30.11		1.00
HWC --> DevLT	-0.05	0.36		5.08
SWC --> DevLT	0.36 *	1.93		5.91
HWC --> RP	-0.39 *	1.69		5.40
SWC --> RP	-0.44	1.47		7.87
DevLT --> RP	0.36 *	1.90		2.02
Control variables				
planned development lead time --> DevLT	0.74 ***	7.59		1.40
slip --> RP	0.27 **	2.30		1.24
plant location --> RP	0.22 **	2.53		1.20
Total effects				
HWC --> RP	-0.41 *	1.74		--
SWC --> DevLT	0.31 ***	2.86		--
SWC --> RP	-0.68 ***	5.06		--
Coefficient of determination (R^2)				
HWC	0.79			
DevLT	0.87			
RP	0.48			
RP (R^2 adj)	0.41			

Notes: N = 46, *** p ≤ .01, ** p ≤ .05, * p ≤ .10, two-tailed tests based on 500 bootstrap resamples.

Further results related to the models M1 through to M11 are provided in the Appendix-B2. In model M1 we summarize the effects of non-significant control variables (sales forecast change, plant age, production technology novelty and linear trend – which is initially significant but disappears in the presence of planned development lead time). In M2 we control for planned development lead time and slip. Both variables turned out to be strong and significant. M3 through M9 each include one factory ID variable to strengthen our claim of non-spuriousness and to justify the inclusion of our last control variable — plant location. In the models M10a through to M10d we tested alternative forms of M10. In contrast to the M10 model, we considered time horizons of 4, 8, 16 and 20 weeks for the calculation of effective utilization in M10a, M10b, M10d and M10e. In model M11, we applied the procedure proposed by Chin et al. (2003) in order to test for an interaction effect between software and hardware complexity constructs on development lead time. However, this interaction effect did not appear to be significant.

3.5.3 Key Findings

There is support for our Hypothesis that hardware complexity is dependent on the level of software complexity (H1). This result corroborates the view that feature implementations are gradually shifting towards software implementations that can run on more generic hardware. Development still follows a hardware-software co-design approach but most of the new innovations in cell-phones originate from new software features and hence determine the hardware requirements.

We observe a negative and significant relationship between software complexity and development lead time (H2) while controlling for planned development lead time. This is an interesting observation and it suggests that software characteristics determine the time expenditures to develop a cell phone. These two findings (H1 and H2) are important since they demonstrate the important role of software in the product development process of new cell phones.

By contrast, the effect of hardware complexity on development lead time is not statistically different from zero (H3). One possible explanation is that software complexity is the main and dominant predictor of development lead time. Hence, hardware complexity is downgraded to a mere enabler without additional explanatory power beyond the software complexity influence.

Furthermore, our results indicate, on average, a negative effect of software complexity on manufacturing ramp-up performance (H4) although the software replication process was initially considered to be negligible. While the direct effect is non-significant there is a significant and negative total effect suggesting that any effect of software complexity on ramp-up performance is mediated by hardware complexity. In Table 12 we provide the results of a bootstrap procedure (Shrout and Bolger 2002, Preacher and Hayes 2008) that provides a nonparametric approximation for the sampling distribution of the different indirect effects. Instead of the product-of-coefficients approach that requires multivariate normality (Preacher and Hayes 2008) we prefer the bootstrapping approach since this method is more consistent with the nonparametric world of PLS. In a first step, we collected the bootstrap output (500 resamples) for the direct and total effects of our model M10. In a second step, we calculated the indirect effects of interest for each bootstrap output (i.e., the product of the paths linking SWC to RP for the three different mediator paths). Finally, we used these values to calculate the percentile bootstrap confidence intervals (Shrout and Bolger 2002, Preacher and Hayes 2008) and the bias corrected confidence intervals (Efron and Tibshirani 1994, Henseler et al. 2008) as shown in Table 12.

Table 12. Results of the mediator analysis

Mediator	Point estimate (indirect effect)	Bootstrapping results (90% CI)			
		Percentile lower	Percentile upper	Bias corrected lower	Bias corrected upper
HWC	-0.35 *	-0.71	-0.06	-0.65	-0.02
DevLT	0.13	0.00	0.35	-0.06	0.30
HWC & DevLT	-0.02	-0.12	0.07	-0.11	0.07

Note: * $p \leq .10$, results are based on 500 bootstrap resamples.

As a result, manufacturing ramp-up performance is dependent on software complexity — e.g. by manufacturing test system yield or software variant readiness — but the effect is mediated through hardware complexity. This is supported by our finding that hardware complexity has a significant direct effect on manufacturing ramp-up performance (H5). We will discuss this effect in more detail in the next section. In any case, our results indicate that the physical characteristics of a cell phone have a negative impact on performance levels in the form of material supply/quality problems or more sophisticated and hence error prone manufacturing set-ups.

Likewise, there is empirical support for Hypothesis 6, stating that manufacturing ramp-up performance decreases as development lead time increases. This finding is in line with our argument that extended development lead times may allow for additional problem solving or pilot production cycles that in turn correspond with improved product and production process maturity levels and ultimately result in improved manufacturing ramp-up performance.

Of the significant control variables, planned development lead time has a positive significant relationship with development lead time. Because software complexity is still significant while controlling for planned development lead time, this suggests that early plans can only provide an imperfect prediction of the actual development lead time. Our results also indicate that products experience a higher manufacturing ramp-up performance on average if they are exposed to late schedule slips. This is likely due to the instance that this sudden and precious gain of time is used for improvements in the material and production status. The results from the factory ID analyses suggest the absence of spurious effects related to plant specific effects that may explain the presented results. All path coefficients remain stable under the individual insertion of each factory ID variable although we see a pattern in the relative influence of factory ID on manufacturing ramp-up performance dependent on the location of the respective factory. On average, Asian facilities tend to perform better than their European counterparts – a finding which is supported by the significant effect of plant location on manufacturing ramp-up performance.

3.5.4 Lifecycle Analysis

Due to the dynamic nature of the ramp-up phase an exploration of the lifecycle behavior is justified. We tested several variants of the above model (M10) for which we used different time horizons in order to calculate the manufacturing ramp-up performance indicator. The various model parameters are recorded in Figure 9.

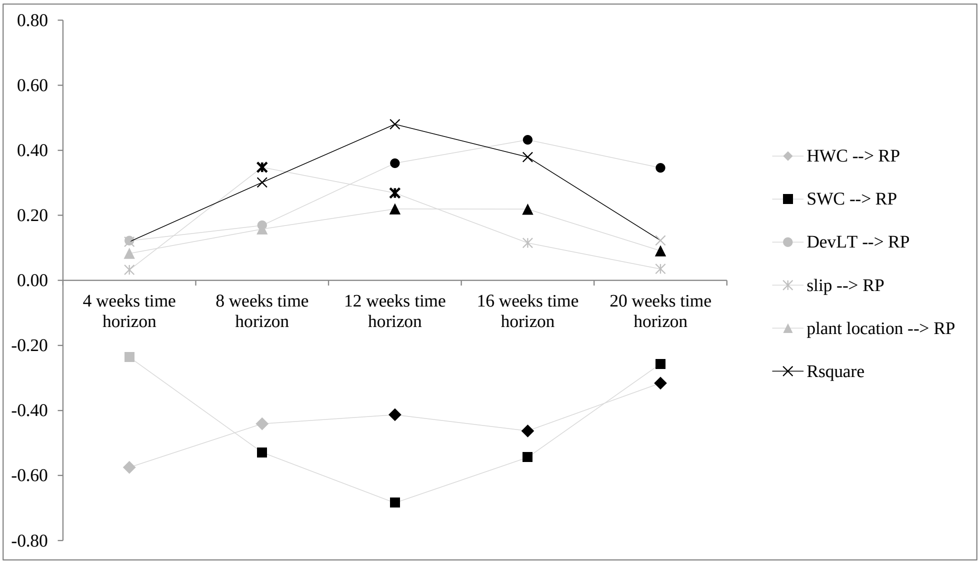
Starting with the model parameters that are calculated over a ramp-up execution period of 4 weeks (T_{RU_EXE} = 4 weeks) we find non-significant path coefficients and only a marginal R^2 value. In other words, our model fails to predict the very early ramp-up phase. This is most likely the result of the chaotic and dynamic environment at this stage that is only partially ascertainable by formal models.

Next, we analyze the parameters over an 8-week period and hence achieve two additional insights. First, the increased R^2 indicates predictive relevance and second, slip becomes strong and significant. Yet, the positive effect of slip on manufacturing ramp-up performance fades out in subsequent models. We will outline the potential mechanism of this effect in the next section but this suggests that factories build up product buffer while they are waiting for the final sales start which in turn helps them to fulfill higher performance levels during subsequent ramp-up stages.

Moving further to the right on the figure (T_{RU_EXE} = 12 weeks) we find the model parameters illustrated that were already discussed previously. Additionally, this model displays the highest R^2 value.

In order to explain the results beyond the 12 weeks' time horizon we experimented with additional variables and discovered that longer time horizons require additional and slightly different predictors. As an example, production plan adaptations and hence production output changes are more likely to occur over longer time horizons in comparison to short term plans in which most resource availabilities are rather fixed. As one would expect, ramp-up specific difficulties diminish and the focus shifts to factors that are related to mass volume planning.

Figure 9. Lifecycle analysis of different model parameters (total effects)



Note: Bold symbols indicate significance, numerical details are provided in the Appendix-B2.

3.6 Discussion and Managerial Insights

Although extant operations management and product development literature implies that ramp-up performance plays a role in the overall performance of a company (Clark and Fujimoto 1991, Pisano and Wheelwright 1995, Hatch and Mowery 1998, Kuhn et al. 2002) we have little systematic and quantitative understanding of the factors that are affecting ramp-up performance. Our findings contribute to this relatively understudied research area in analyzing the combined and lifecycle dependent quantitative relationships between product development process characteristics (i.e., development lead time), product characteristics (i.e., product complexity), slip and manufacturing ramp-up performance.

First, our findings suggest that the mechanisms by which product complexity characteristics affect manufacturing ramp-up performance differ significantly. Hardware complexity seems to be a continuous and steady source of difficulty for manufacturing during the whole ramp-up phase as identified in our lifecycle analysis. This suggests that problem solving cycles related to physical product characteristics (e.g., design faults that create assembly failures or low yield levels at supplier operations) are slow and cumbersome. While the root causes might be identified quickly; the actual engineering change is mostly tardy as solutions often require new or improved materials but long lead times or excessive pipeline inventory slows down the implementation process. Based on our experience this may take up to several weeks or even months during which production teams have to cope with the current situation and hence often fail to deliver output on plan. Software complexity on the other hand demonstrates a completely different lifecycle pattern. After the production release of the initial software and the start of the replication process we do not experience any negative effect of software complexity on manufacturing ramp-up performance. However, as soon as the initial phase is over — a phase in which only a limited amount of customers have been served — we find a considerable negative influence on manufacturing ramp-up performance. At least two assumptions are consistent with this result. New and complex cell phone software must be compatible with other products in the network (Chiesa et al. 2002) and frequently requires changes on the network side. Often, these modifications are not simultaneously available in all networks and hence pose a potential delay for second wave approvals. Also, the creation and verification of customer specific variants is a more complicated process in the presence of high software complexity. More options are available and side effects are more likely to occur thus leading to delays in production execution and to decreased manufacturing ramp-up performance. However, the overall problem solving cycles regarding software issues are shorter than those caused by hardware problems since the negative effect of software complexity on manufacturing ramp-up performance fades out rather quickly. This is consistent with the software variant creation release cycle in Nokia that may take several days or weeks at the most.

Second, we shed light on the relationship between product complexity and development lead time in the cell phone industry (in consideration of the fact that our sample provides a very homogeneous in-house manufacturing depth). The context of our study is representative for the consumer electronics industry in which the influence and importance of software has increased substantially in the past decade and time to market is a factor of critical importance. As already lined out in the introduction of this chapter, the majority of new features are developed in software and hence determine the development schedules to a large extent. Examples are browsers, mobile TV, gaming, augmented reality or dual SIM functionality as well as the option to provide and access local relevant content (e.g., social networks). Hardware on the other hand becomes a commodity available from various sources and in different configurations. This circumstance requires the involvement of purchasing managers in the product development process. However, since purchasing managers have a strong focus on material cost, their involvement can sometimes correlate negatively with the adherence to development schedules. For example, the implementation of second source components or the adjustments of existing code to cost efficient but slow processors require considerable time and effort for coding, testing and the implementation. Another reason for the strong effect of software complexity on development lead time – while controlling for planned development lead time – might be related to the presence of planning fallacy. Software teams seem to make decisions based on delusional optimism rather than on a rational weighting of gains, losses, and probabilities (Lovallo and Kahnemann 2003). This often results in planned development lead times that accentuate positive assumptions as they were created in an intuitive and unobjectionable process and are therefore often unlikely to hold.

Third, the results highlight that development lead time – considered as a resource and hence as a predictor – in combination with given levels of product complexity has a significant positive effect on manufacturing ramp-up performance. Thus, shorter development lead times imply that project activities have to be executed faster than normal and project managers are less able to predict activity outcomes. Hence, it is generally more difficult to achieve on-time performance (Swink 2003). As already mentioned above, development lead times are driven by software complexity. In consequence, this shifts hardware development activities away from the critical path enabling projects to fine-tune hardware activities while waiting for the software release. We also experimented with different model variants and observed that development lead time has a positive effect on manufacturing ramp-up performance, but solely in the presence of software complexity (i.e., the presence of a direct path between software complexity and manufacturing ramp-up performance in our model). In other words, our model suggests that the exclusion of hardware complexity from the critical path during new product development has a positive impact on product maturity and hence on manufacturing ramp-up performance. For example, suppliers that are responsible for physical parts (e.g., plastic covers) can run multiple test-batches until they are sure that the process works faultlessly and that they can match the desired quality levels. This is in contrast to projects with highly compressed schedules in which fine-tuning activities often continue during the ramp-up phase, hence leading to discontinuous output and quality instabilities. Also, we believe that more design-build-test cycles or additional time for evaluation activities between the cycles (e.g., for second source materials) may lead to higher product maturity levels and ultimately to stronger and more sustainable manufacturing ramp-up performance as indicated by the lifecycle effect of development lead time on manufacturing ramp-up performance in Figure 9. According to Wheelwright and Clark (1992) prototyping and its role in design-build-test cycles is a core element of development and an area that offers major opportunities for management to improve the effectiveness and efficiency of their development process.

Finally, we observe a positive relationship between slip and manufacturing ramp-up performance which supports our argumentation that late schedule slips are advantageous for manufacturing ramp-up performance. There are several possible theories for why this relationship exists. Most late schedule slips are the result of delayed software approvals or material deficiencies (Almgren 2000, Kuhn 2002). For example, the flexibility of software makes it vulnerable to late additions or changes in order to correct for hardware problems (Rauscher and Smith 1995) or in order to quick-fix errors that are detected during the product acceptance phase. Material deficiencies are more likely to occur just before the ramp-up start because suppliers switch from pre-production tools to mass-production tools for which only limited experience exists. In any case, these issues occur late, often unexpectedly and may lead to ramp-up delays. On the other hand, there is a strong managerial tendency, motivated by higher gross-margins of new products, to start production gradually. Despite lost capacity for existing products and rising inventory levels for semi-finished products the potential gains in production experience, material quality and new product availability (semi-finished product buffers can be converted into final products via simple assembly and "re-programming" steps as soon as the necessary approvals are in place) compensate for negative aspects. According to Terwiesch and Bohn (1998), running engineering trials and efforts regarding the improvement of yield and production speed at the beginning of the ramp-up phase might limit the uptime in the short run, but will often lead to an increased performance during the rest of the ramp-up period. In other words, late schedule slips do not only enable factories to ramp-up faster after the actual ramp-up start but it also enables them to boost their throughput as demonstrated by the strong impact of slack at the beginning of the ramp-up period. However, as soon as experience levels saturate and buffers are used up as shown in the lifecycle analysis this positive effect on manufacturing ramp-up performance fades out.

While the primary focus of this research is to predict ramp-up performance levels and to explain the phenomena around this subject, several managerial issues and practical implications arise from the work. Our findings highlight the drivers of development lead time in cell phone projects. While planning accuracy is potentially affected by the presence of planning fallacy in the software domain and while it is best tackled by taking an outside view (Lovallo and Kahnemann 2003), actual development lead time is determined by software complexity. Thus, the managerial implication of this finding is that shorter development lead times are more likely to be achieved if firms focus on strategies to either cope with software complexity or to decrease it instead of decreasing hardware complexity by using fewer and less novel components. A common approach in time-paced markets where new products or upgrades are released on a regular basis is to slip everything that cannot be completed in time to the next product in the sequence (Eisenhardt and Brown 1998). Yet we do not argument that all sources of software complexity are counterproductive and must therefore be eliminated or reduced to lower levels. We rather claim that firms – especially if operating in highly competitive and dynamic markets – need to understand the potential impact of their choices and use available best practices (e.g., Swink 1998) in order to accommodate to the higher levels of complexity that the market imperatives entail. In this sense, software postponement may be a successful approach, although it received only little attention. In other words, manufacturing and production testing activities should be independent of the product software. They should rather use a basic core software for manufacturing before the final customer specific software package is programmed into the phone at the last possible step in production. This allows firms to ramp-up production of semi-finished products as soon as the product hardware is ready even if the final software is not yet released for production. This process continues until a maximum buffer level is reached or until the final software package is released for production. In a next step the semi-finished products are quickly converted into end products via simple re-programming steps just before packing. While this approach does not necessarily decrease development lead time it increases early product availability and hence ramp-up performance. This is partly due to the potential consumption of product buffers but also due to advances in pre-ramp-up learning. However, this effect is dynamic and diminishes quickly.

Also, our conclusions underscore the importance of the right product-factory fit and the relevance of software variant management. We feel that the division of complexity into hardware and software elements provides a suitable approach to guide management decisions in order to apply the most efficient strategy for any particular product. For example, products with high hardware complexity may gain considerably from DFM activities, early manufacturing involvement and a careful selection of the lead factory with particular focus on the right product-factory fit — the fit between the demands a product is likely to make upon a factory and the existing competence of the factory to which it is to be introduced (Langowitz 1988). Such an approach, however, is unlikely to be successful in coping with software complexity as this would rather require efficient and proactive software variant management activities.

Finally, our findings underscore the importance of development lead time management with regard to manufacturing ramp-up performance. Managers in the consumer electronics industry are tempted to accelerate product development in order to launch products just before special events such as industry trade shows or high peak sales periods (e.g., Christmas). While the timing of revenues critically depends on development lead time (time-to-market) firms must be careful not to over-accelerate product development. Over-acceleration can have a significant negative impact on customer relations and competitor market share if firms fail to achieve required manufacturing ramp-up performance levels (time-to-volume). Although it is known that the fast introduction of high-tech products to the market helps to achieve overall commercial success (Mallick and Schroeder 2005), creating too much overlap between phases makes it difficult for teams to anticipate changes possibly resulting in products that are not optimized for volume manufacturing by the time of their launch (Krishnan et al. 1997). For example, products that are targeted for Christmas sales (i.e., ramp-up start in September) may not gain much from overly compressed schedules and an earlier product launch in August when the demand is still only moderate. In such a case, firms may gain more if they allow their teams to execute as planned and to focus on manufacturing ramp-up performance since the volumes that are missed during the Christmas period are ultimately lost. However, the relationship between gains in manufacturing ramp-up performance and speed of product development is complex and deserves further research attention in order to weigh up launch timing against development completeness (Kalish and Lilien 1986).

3.7 Conclusions

This chapter examines the quantitative interrelationships between product development process characteristics (i.e., development lead time), product characteristics (i.e., product complexity), slip and manufacturing ramp-up performance over different time horizons. We complement previous studies regarding ramp-up performance in three ways. First, we demonstrate that software complexity is the dominant driver for development lead time in cell phone projects. Second, we identify development lead time as an important predictor for manufacturing ramp-up performance. While longer development lead times facilitate higher product maturity and thus sustained manufacturing ramp-up performance, later market introductions of new products imply a negative impact on revenue inflows. Third, our model also suggests that late schedule slips, although disastrous for customer relations in which due dates are crucial, provide the opportunity to build up (semi-finished) product buffers which in turn increase the initial ramp-up performance. In conclusion, we contribute to the field of operations management by offering a more comprehensive and enriched understanding of the drivers for development lead time and manufacturing ramp-up performance in the cell phone industry. We also contribute to the existing research by providing an alternative view into the specific and lifecycle dependent effects of development lead time, product complexity and slip on manufacturing ramp-up performance. Thus, our insights support management efforts to anticipate the consequences of product design decisions, to predict development schedule risk levels and to make informed decisions about production volume commitments.

Although our findings are firm specific we believe that our results can also be generalized to fit the wider consumer electronics industry because: (1) modern consumer electronics products like hi-fi systems, game consoles, cameras and flat screens share similar product and development characteristics with cell phones, (2) our operational data were taken from different geographical development centers with different cultural and managerial properties and (3) our results extend existing empirical work from other industries.

While this study makes a significant contribution to the academic literature and provides guidance for managerial practice, there are also limitations that provide opportunities for further research. First, our conclusions are based on a limited number of real life cases that were carried out in a single firm. A wider analysis including different firms from the consumer electronics industry utilizing a larger sample size might reveal additional effects and thus potentially enhance the capability to make generalizations that exceed the scope of the consumer electronics industry. Second, with respect to the predictors that are involved in our study we believe that there are further factors such as organizational forces or supply chain elements (as outlined in Table 1) that may contribute to development lead time or ramp-up performance. A fruitful extension could identify and specify these factors and assess their impact on the given model parameters to advance our theoretical understanding of the contingent relationships. Third, as we mentioned earlier, firms need to make a conscious choice between project acceleration and ramp-up performance. This circumstance prompts for formal models to find the optimal level of project acceleration that maximizes the total revenue inflow for given levels of product complexity. Finally, future research should revisit the effectiveness of knowledge transfer across projects although we did not find an impact of linear trend on manufacturing ramp-up performance in our study. We might expect to find a weak integration of knowledge from past related projects, since products develop through a sequence of changes that tend to build on past experience (Clark 1985). Therefore, the operational and strategic importance of knowledge management (Sherman et al. 2005) deserves special attention, most notably with respect to knowledge transfer across projects and across sites.

Chapter 4

Uncovering Plant Specific Differences during New Product Ramp-ups

Abstract: *We present a framework for the exploration of selected supply-chain structure characteristics and their impact on manufacturing ramp-up performance. Our findings indicate that the internal configuration and organization of key suppliers (i.e., proximity of tool shops and their engineering capabilities to the part manufacturing location), the level of automation within a plant and the time period in which a new product is ramped-up are important drivers of manufacturing ramp-up performance. Furthermore, the comprehensive analysis of these combined effects provides an explanation for the on average lower performance of European manufacturing plants in comparison to their Asian counterparts. Since it is the main objective of the high-tech industry to achieve full-scale production and thereby time-to-volume targets as quickly as possible, our results suggest that the selection of the ramp-up factory is a crucial decision within the product development process for new products.*

4.1 Introduction

New product development is the life-blood of high-tech manufacturing (Mallick and Schroeder 2005). In an environment of growing global competition, shrinking product life cycles, fragmented markets, rising cost pressure and frequent technological changes the successful development and introduction of new products that meet consumer needs are key capabilities for success. In spite of significant progress in product development, operations management and supply chain management the transition from development to mass-production – the ramp-up - remains a major challenge but also an opportunity to gain a competitive advantage.

As we show in chapter 1, ramp-up management in general has already been described and analyzed in the literature (Clawson 1985, Langowitz 1987, Clark and Fujimoto 1991, Pisano 1995, Terwiesch et al. 1998, Almgren 2000, Kuhn et al. 2002, van der Merwe 2004, Schuh et al. 2005) and there are also contributions that examine the specific interrelationships between certain supply chain characteristics, operations characteristics and ramp-up performance. For example, Clark and Fujimoto (1991) performed a global field study to understand and analyze new product development in the automobile industry. Although they focused on the effects of strategy, organization and management on product development their findings also revealed manufacturing-specific factors that influence ramp-up performance. In their view, excellence in manufacturing capability (the ability to make things rapidly and efficiently) results in rapid prototype cycles, fast tool development and ultimately in effective ramp-up and full-volume production. In addition, Clark and Fujimoto (1991) found indications that outstanding manufacturing capabilities result in faster time to market, fewer engineering hours and higher quality. Manufacturing capability in terms of physical resource capabilities and organizational capabilities was also highlighted as an influential factor on the outcome of the initial production of new products by Langowitz (1988). Another large study by Kuhn et al. (2002) identified, among other factors, the robustness of the production process as a critical determinant of ramp-up performance and an arena for further research. Comparable findings were documented by Schuh et al. (2005) with the ambition to identify successful approaches and concepts in ramp-up management. The studies of Hayes et al. (2009) and Hayes and Clark (1986) are more specific and also supported by empirical data. They explored the sources of differences in productivity at factory level with focus on structural factors (factory age, size, location, unionization) and managerial factors (equipment policies, quality policies, inventory policies, workforce policies, confusion). In essence, their results reveal that the amount of work-in-process and the extent of confusion engendering activities are significant sources of variation in total factory productivity. In another study by Pesch et al. (1996) similar operations characteristics (plant size, number of product lines, plant age, number of processes, type of processes) were investigated with the focus on the compromising effect of these environmental variables on manufacturing performance. Their empirical results provide evidence of a relationship between the number of product lines, the number and type of manufacturing processes and plant focus. A broader assessment of supply chain factors that drive plant level performance was drawn up by Bozarth et al. (2009). They specifically find that upstream complexity, internal manufacturing complexity and downstream complexity all have a negative impact on the performance of the manufacturing plant. These findings reveal various supply chain characteristics that affect performance on plant level and hence support our study that intends to filter out the key characteristics in the specific context of manufacturing ramp-up performance. In addition, we expect to uncover plant specific effects with a combined assessment of the identified key characteristics.

The remainder of this chapter is organized as follows. First, we present our conceptual model and state our formal Hypotheses. Next, we outline our research setting and explain how our variables are measured before we start to present our results. We end the chapter with a discussion of our findings, investigate the implications for managers, point out limitations and provide directions for further research.

4.2 Conceptual Model and Hypotheses

Figure 10 depicts the supply chain structure characteristics examined in this study. While these characteristics can be examined at different levels, we decided to examine them empirically at the individual product level. In other words, the unit of analysis is the individual cell phone that is developed, manufactured and sold by our case firm. At this level of analysis, we focus on the identification of differences in manufacturing ramp-up performance that emerge from within the plant (operations characteristics), or from the connection of a plant with its key suppliers (supply characteristics).

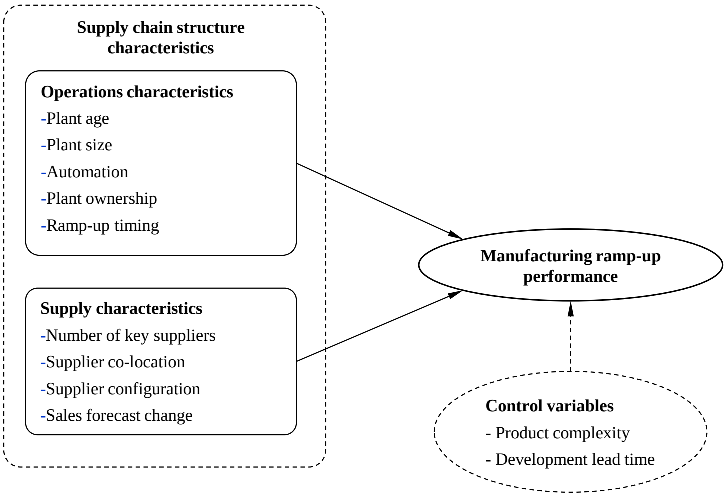


Figure 10. Conceptual Model

4.2.1 Operations Characteristics

The majority of operations characteristics that according to our Hypothesis influence manufacturing ramp-up performance (Figure 10) are selected based on the focused factory concept introduced by Skinner (1974). He argues that a focused factory has a limited set of demands that are placed on it by different products, processes, customers and manufacturing requirements and hence maintains a distinctive competence and establishes a competitive advantage. Environmental variables that are commonly thought to be related to manufacturing plant focus and ultimately manufacturing ramp-up performance are plant age, plant size and the type and number of manufacturing processes in the plant (Pesch and Schroeder 1996). In addition, we consider the ownership of the plant and timing aspects regarding new product ramp-ups in our model.

Plant age. Skinner (1974) and Pesch and Schroeder (1996) discuss how factories often lose plant focus over time. They argue that a factory typically starts out with a fairly well-defined purpose but plant focus weakens in the course of time as managers attempt to fulfil various and often conflicting demands from different functions. The controlling function may for example push a plant manager to reduce cost by limiting new investments and standardize the manufacturing line layout in order to achieve high production volumes and hence economies of scale. On the other hand, product development teams may press the plant manager to install special-purpose equipment (e.g., customized production test systems) and setup product specific line concepts (e.g., with advanced order penetration points) to introduce new product designs and technologies. Over time, this dilutes the originally well-defined priorities and initial focus of the plant. On the other hand, plant age might correlate with accumulated learning / experience and hence may improve the ability of a plant to ramp-up new products successfully. Hence we state:

HYPOTHESIS 1. *Plant age is associated with manufacturing ramp-up performance.*

Plant size. The literature suggests that small plants are generally more focused than larger plants because larger plants tend to produce more product types, have more customers, and technologies (Pesch and Schroeder 1996). Another reason was proposed by Schmenner (1983) who notes that some plants become large over time due to on-site expansions in order to cope with increased capacity needs. In response, multiple product requirements and inefficient plant layouts are some of the factors associated with plant size that detract from plant focus and hence performance. For example, any compromise between the vast variety of product requirements (e.g., incoming material package type, number of assembly and screwing places, size requirements of the assembly places, number and type of production test phases, etc.) and the requirements of a standardized manufacturing line configuration throughout the entire plant may lead to inefficiencies and disturbances in the ramp-up of new products. However, plants that are capable to produce multiple products with various different requirements may have a broader skill / resource capacity and are hence more proficient in coping with new product ramp-up challenges. In addition, larger plants are more likely to be able to allocate and mobilize additional resources in the short term to support critical ramp-up activities. Hence we hypothesize the following:

HYPOTHESIS 2. *Plant size is associated with manufacturing ramp-up performance.*

Automation. The automation of manufacturing systems can be defined as a substitution of manual labour with automatic facilities and equipment so that the system can operate with fewer labor hours per produced unit (Vonderembse et al. 1997). In cell phone manufacturing, this usually involves the adoption and implementation of various advanced manufacturing technologies, such as special purpose machinery, robotics or automatic assembly cells. However, there are controversial opinions regarding the impact of manufacturing system automation on performance. On one hand, automated manufacturing systems are often regarded as highly efficient, potentially improving the competitiveness of manufacturing companies (Säfsten et al. 2007) and offering some localized benefits in terms of quality, cost and productivity (Liao and Tu 2008). On the other hand, empirical analyses indicate that manufacturing system complexity may affect performance in a negative way (Guimaraes et al. 1999), especially within an increasingly turbulent competitive environment. According to Guimaraes et al. (1999), even moderately complex manufacturing systems will show frequent stops and poor availability unless they are operated by the very same experts who designed the system. Apart from equipment availability, automated manufacturing systems are also very sensitive to variations in the quality of the parts – something that happens frequently in early ramp-up situations. For example, slight variations regarding the position or adhesion force of protective tapes, dimensional/color variations of cover parts or deviations in the delivery conditions of suppliers will typically not have any effect on the work of a human operator. In the case of automated systems such as robots, however, these variations can result in enormous difficulties during the early ramp-up phase and the lack of flexibility can cause unstable assembly operations. As manufacturing ramp-up performance will depend on the productivity of the assembly process, we state the following Hypothesis:

HYPOTHESIS 3. *Manufacturing system automation negatively affects manufacturing ramp-up performance.*

Plant ownership. The existing literature reveals that an appropriate degree of outsourcing is an important economic and strategic decision, affecting the manufacturing efficiency and competitiveness of a firm (Leachman et al. 2005). In our consideration, the degree of outsourcing involves the manufacturing of semi-finished products at contract manufacturers along with the associated component procurement process. Such an enhancement of manufacturing capacity provides the capability to adjust the scale and scope of the manufacturing network and avoids the necessity of large investments in durable assets under volatile market conditions. However, outsourcing also has several pitfalls and according to Leachman et al. (2005), high levels of outsourcing lead to disproportionally lower levels of manufacturing performance in a firm. For example, poor vendor management skills may lead to a loss of management control, resulting in higher costs, loss of institutional knowledge and the risk of becoming too dependent on vendors to perform operational routine tasks (Bardhan et al. 2007). Other risks can include the challenging knowledge transfer and information management process across inter- and intra-organizational boundaries (Bardhan et al. 2007). Moreover, the required capabilities for ramp-up support and improvement rely on detailed firm-specific knowledge or on specific knowledge about the technical characteristics of a given cell phone that contract manufacturers may not have as a result of their pooling strategy. Therefore, we hypothesize that in-house production provides better communication, coordination and knowledge transfer within an organization which in turn results in better product-factory fit, problem solving ability and ultimately in a better manufacturing ramp-up performance. Hence, we formally state the following:

HYPOTHESIS 4. *Plant ownership positively affects manufacturing ramp-up performance.*

Ramp-up timing. As cell phone manufacturing is exposed to large seasonal volume fluctuations, manufacturing operations experience substantially higher production rates during the months of September, October and November in order to fulfill the global Christmas demand. This circumstance can affect new product ramp-ups due to tight supply with raw materials and components, because production engineering resources are fully loaded with the prevailing production or because priorities are allocated based on general strategic considerations (i.e., not based on new product ramp-ups). In contrast, ramp-ups during low volume seasons can benefit from adequate managerial support and resources and hence reduce manufacturing failures and WIP while continuous improvement projects can be started at the same time. This leads to our fifth Hypothesis:

HYPOTHESIS 5. *Ramp-up timing (product ramp-ups outside the peak season of the year) positively affects manufacturing ramp-up performance.*

4.2.2 Supply Characteristics

Our Hypotheses are based on previous research that points to the importance of supply configurations and in particular to the number of key suppliers, their location, their capabilities and their dynamic behavior in the context of manufacturing ramp-up performance (Clark and Fujimoto 1991, Swink 1999, Kuhn 2002, Hayes and Clark 1985, Bozarth et al. 2009). As the supply characteristics for product specific components are most relevant in the context of ramp-up performance (Pufall et al. 2012b), our further discussions refer to key suppliers who play a particular role in the development and supply of product specific components that are explicitly developed for the use in specific products (e.g., plastic covers, metal parts, antenna elements). Common components that are available in the market from multiple sources and that are developed independently of a target product are out of the scope for the subsequent discussion.

Number of key suppliers. According to Bozarth et al. (2009), adding suppliers increases the number of information flows, physical flows and relationships that must be managed. In addition, multiple suppliers for product specific parts expose sparse development resources to a wide range of potentially aggravating factors such as additional verification and approval cycles. However, in order to sustain bargaining power and to mitigate supply risks, purchasing managers often request second sources for critical parts. The availability of critical parts from different sources decreases the risk of supply shortages during ramp-up situations and also helps to stimulate competition between suppliers. Delivery inabilities or issues regarding material quality on the part of one supplier provide an opportunity for other suppliers to excel on these dimensions in order to gain volume share and hence additional profit. Thus, we believe that the negative effects of increased development and order management efforts are clearly compensated by the benefits of improved supply availability/quality in the framework of a multiple source configuration (i.e., more than one key supplier for product specific parts). We formally state this in our sixth Hypothesis:

HYPOTHESIS 6. *The number of key suppliers positively affects manufacturing ramp-up performance.*

Supplier co-location. Co-location aims at integrating the forward physical flow between suppliers and customers (Cagliano et al. 2004) and requires a close coupling of the production systems between both parties. While this concept has been discussed for mass-production conditions, manufacturing ramp-up performance can also benefit from logistical proximity in several ways. First, safety stocks and hence the delay between fabrication and use is positively affected since safety stocks need to protect against shorter lead times. The decreased delay between fabrication and use also results in fewer opportunities for deterioration and in less information loss regarding quality. As stated in the just-in-time philosophy (Schonberger 1982), material quality problems are for example less likely to cause utilization losses in the target manufacturing plant if suppliers and customer operations are co-located. In that case, supplier teams can visit the customer operation in little time, gather all relevant data, implement improvements in their own component manufacturing line and deliver new or modified parts to the customer operation within hours. In contrast, long supplier lead times due to remote supplier locations are found to have a significant negative impact across various performance measures (Bozarth et al. 2009). This leads to the following Hypothesis:

HYPOTHESIS 7. *Supplier co-location positively affects manufacturing ramp-up performance.*

Supplier configuration. In typical cell phones, most of the product specific parts (i.e., all structural frames, connectors and most of the outer covers) are manufactured by plastic injection molding. This manufacturing process uses thermoplastic resin which is fed into a heated chamber where it is melted. In the next step, a plunger forces the melted plastic into a cooled mold cavity where it solidifies. A painting process in which the parts get their final surface finish follows before the parts move through an assembly line in which additional components are assembled (e.g., foams, stickers, gaskets and even electromechanical parts such as connectors and speakers). Finally, the parts are packed for shipment to the customer manufacturing plant. Molds and selected assembly tools are made out of specialized materials which require precision machining in dedicated departments - often called tool shops. Since the mold has a large influence on the dimensional accuracy and surface finish of the parts, the design and manufacturing of molds is a crucial activity that requires sophisticated CNC machinery as well as dedicated engineering teams. Before and even during the ramp-up phase these specialized teams are responsible for the fine tuning cycles concerning the mold and for the support of mass-production personnel in order to achieve the desired quality levels. As most molds require several polishing and dimensional fine-tuning cycles in the tool shop, the physical proximity between both departments becomes an important factor. As Pisano and Shih (2009) note, product and process innovations are intertwined and process engineering expertise depends on daily interactions with manufacturing. Hence, we hypothesize that the essential factor in a ramp-up context is not just the physical distance between a supplier and its customers operation (co-location) but also the internal configuration of the supplier (i.e., the way how tool shops and their engineering capabilities are integrated into the part manufacturing network). Supplier configurations in which tool shops reside next to the parts manufacturing location may provide shorter feedback loops, problem solving cycles and reduced machine/assembly line stoppages compared to scattered setups. Therefore we state the following:

HYPOTHESIS 8. S*upplier configuration resource proximity positively affects manufacturing ramp-up performance.*

Sales forecast changes are a significant source of dynamic complexity in the supply chain and were found in terms of plan instabilities to be relevant to plant-level performance (Bozarth et al. 2009). This is because rising levels of volume forecasts increase the size and scope of a plant's demand management and order management activities to establish elevations in production schedules. Apart from the influence of rising forecast changes on production schedules there may also be an effect on production execution. For example, factories will respond to decreasing demand forecasts with reductions in output (to avoid finished goods inventories) and material orders compared to the original plans. This may cause disillusion on supplier side (i.e., suppliers rank down the product in priority as a result of diminishing revenues) and distort ramp-up performance although the overall supplier and manufacturing ramp-up performance might be fine. Accordingly we state:

HYPOTHESIS 9. *Sales forecast changes positively affect manufacturing ramp-up performance.*

4.3 Measures

Manufacturing ramp-up performance (dependent variable). Following the existent ramp-up literature (Langowitz 1988, Clark and Fujimoto 1991, Terwiesch 1999, Almgren 2000, Kuhn et al. 2002, Merwe 2004, Schuh 2005), we measure manufacturing ramp-up performance in terms of output against plan. More precisely, we calculate it as the ratio between the produced quantity during the ramp-up period and the planned quantity at the beginning of the ramp-up period. Both variables are taken from a production database that contains highly reliable data concerning both planned and actual numbers.

4.3.1.1 Operations Characteristics Measures

Plant age is measured as the time in years a plant has been in operation prior to the ramp-up start of each product. *Plant size* represents the total area allotted in square meters to the manufacturing and to the storage of manufacturing-related materials. The variable *automation* is coded as a dummy variable with 1 indicating that a substantial share of the manufacturing process is automated versus fully manual assembly lines. *Plant ownership* is a dummy variable with 1 indicating in-house facilities (i.e., Nokia owned) and 0 indicating contracted facilities. In our sample, three of the nine facilities were owned by contract manufacturers which were responsible for the manufacturing process up to a generic product level. Afterwards, the units were shipped to in-house facilities for the final configuration and distribution. *Ramp-up timing* is another dummy variable with 1 indicating all months of the year except for September, October or November.

4.3.1.2 Supply Characteristics Measures

To establish our variable *number of key suppliers,* we counted the number of product specific part suppliers that are qualified and ready to supply product specific parts to the ramp-up factory at the start of the ramp-up phase. This information is derived from the sourcing parts list and project documentation that also provides the data for two other variables: *supplier co-location* and *supplier configuration*. Supplier co-location is measured as the transportation lead time in days between the respective supplier and the ramp-up factory, whereas supplier configuration is coded as a dummy variable with 1 indicating that tool shop and part manufacturing are closely connected within a supplier and 0 otherwise. Finally, *sales forecast change* is defined as the ratio between the forecasted demand over the ramp-up execution period and the forecasted demand over the same period but collected 12 weeks before ramp-up start.

4.3.1.3 Control Variable

Since we intend to identify plant level supply chain structure characteristics that affect manufacturing ramp-up performance and that can be generalized across product categories, we need to control for aspects of product complexity and development lead time. *Product complexity* reflects the technical complexity of a product and is represented by the first component of a principal component analysis with seven input variables: (1) the number of product specific components, (2) the number of common components, (3) the extent of parts coupling between all electrical components, (4) the degree of product novelty, (5) the size of the SW code, (6) the degree of SW novelty and, (7) the number of SW errors. This approach retains the nature of the original variables but reduces their number in order to enhance robustness of the subsequent multiple regression analysis concerning statistical power and multicollinearity. *Development lead time* refers to the elapsed time in days between the M0 milestone (end of concept development) and the M3 milestone (start of production ramp-up) as described in section 3.2.1. Further details about the variables in general are provided in section 2.2.2. Please note that we do not control for in-house manufacturing depth as this aspect is homogeneous throughout our sample.

4.4 Results

To enable a comparison of effect sizes, we standardized all variables (mean = 0, variance = 1) before running the regression calculations. This is useful as our data is recorded in different scales (e.g., component count uses pieces, plant age uses years). Unstandardized results, descriptive statistics and pairwise correlations are provided in Appendix-C1. In general, correlations are as expected and moderate in magnitude. The multivariate regression results are presented in Table 13. The assumptions of our multiple regression models were tested with several statistical methods. First, all data panels were screened for abnormal observations to avoid bias in the regression calculations. Next, the predicted values were plotted against standardized residuals to show a random scattered pattern, supporting the assumption of linearity and homoscedasticity. For each regression, we calculated variance inflation factors to rule out multicollinearity problems. The resulting variance inflation factors (< 5.1) indicated no significant multicollinearity effects for any of the models (Hair et al. 2006). In addition, the normality of the error term is supported by the appropriate histograms and normal probability plots.

In column 1 (R1), we present the base result, based on the inclusion of our control variables. Product complexity has a significant negative influence on manufacturing ramp-up performance in all the regression models which is in line with our reasoning that more complex products are harder to ramp-up (refer to chapter 2) and previous studies (Pufall et al. 2012a, Pufall et al. 2012b). Likewise, development lead time has a significantly positive effect on manufacturing ramp-up performance as already shown in chapter 3. While this effect always remains strong, its significance starts to weaken in the subsequent models (R2 and R3).

In column 2 (R2), we include the measures of our operations characteristics. Neither do plant age, plant size or plant ownership add to model fit nor do they generate statistically significant results. This reflects the inconclusiveness of the theory that provides arguments for and against an effect of plant age, plant size and plant ownership on manufacturing ramp-up performance in this case. In addition, the management in our sample plants has possibly made efforts to focus the older or larger plants that are included in this study by renewing equipment, by aligning them with other plants and by providing them with a clear direction.

However, we find automation and ramp-up timing to be significantly different from zero in our statistical analysis. This supports Hypothesis 3 and Hypothesis 5.

In column 3 (R3), we additionally include the measures of our supply characteristics. The results suggest that the number of key suppliers and their location are statistically insignificant and hence not relevant to explain differences in manufacturing ramp-up performance between plants. By contrast, supplier configuration has a very strong, positive and significant effect on manufacturing ramp-up performance. Hypothesis 8 is supported by this result. The effect of sales forecast change is directionally correct and statistically significant which supports Hypothesis 9. The explained variance sums up to 47%.

Table 13. Regression results for manufacturing ramp-up performance

	R1	R2	R3
Control variable			
Product complexity	-0.703*** (0.142)	-0.654*** (0.186)	-0.495** (0.188)
Development lead time	0.277* (0.142)	0.233 (0.147)	0.167 (0.150)
Operations characteristics			
Plant age (H1)		0.079 (0.199)	-0.043 (0.205)
Plant size (H2)		0.219 (0.233)	0.127 (0.239)
Automation (H3)		-0.343** (0.154)	-0.292* (0.168)
Plant ownership (H4)		-0.061 (0.213)	0.056 (0.215)
Ramp-up timing (H5)		0.211 (0.130)	0.262* (0.131)
Supply characteristics			
Number of key suppliers (H6)			-0.052 (0.132)
Supplier co-location (H7)			-0.038 (0.225)
Supplier configuration (H8)			0.382* (0.198)
Sales forecast change (H9)			0.210* (0.118)
R^2(adj)	33.90%	40.10%	47.00%

Notes: N = 46, values in parentheses are standard errors, *** $p \leq .01$, ** $p \leq .05$, * $p \leq .10$, two-tailed tests. All VIF values < 5.1.

4.5 Discussion and Managerial Insights

The key objective of this study has been to investigate the effect of supply chain structure characteristics on manufacturing ramp-up performance using operational data from the cell phone industry. We now evaluate the significant characteristics as shown in Table 13 from top to bottom in more detail.

The strong negative effect of automation level on manufacturing ramp-up performance suggests that it is easier for manual lines to absorb the various ramp-up difficulties in cell phone manufacturing. In other words, positive effects of automation can only be expected under appropriate levels of automation (Säfsten et al. 2007). While automated systems are often regarded as highly efficient for high volume manufacturing, their inflexibility seems to limit the number of demands that a line can accept during highly dynamic periods. For example, small variations in the quality of parts (e.g., dimensional or color variations) are a common issue during new product ramp-ups. Such deviations from the norm may interrupt the production flow as automated grippers, fixtures, assembly robots or transportation systems cannot be configured and trained prior to the ramp-up start with material that represents the full range of variations commonly found in mass-production material. This results in laborious modification and fine-tuning activities, dispute over particularly skilled but sparse engineering personnel and longer downtimes because backup systems are less likely to be available in automated environments than in manual systems. We also observed that product development teams tend to use manual assembly solutions during the prototyping phase due to their advantages regarding cost, flexibility and manufacturing lead-time. However, this has a negative effect on the verification process in manufacturing as industrial engineering teams lack the necessary time for development and fine-tuning. Altogether, our findings and own observations suggest that manual systems in cell phone manufacturing are more adaptable in a ramp-up context. They require less fine-tuning and engineering support and it is a lot easier to install or duplicate them in order to accommodate for the transition to mass-volume production.

Also, our results suggest that manufacturing ramp-up performance is lower during the peak season from September to November. Since the time period of September to November is characterized by higher production volumes (to serve the Christmas demand), plants generally experience shortcomings in engineering support and material availability. The available engineering resources in-house and at the suppliers will have to manage a larger number of jobs and activities during such time periods, leaving less time to support new product ramp-ups. At the same time – and particularly regarding common components – there will be tight material supply because suppliers experience similar demand peaks from other customers. Also, there are cases in which both product development activities and ramp-up volume plans are aggressively pushed forward in order to capture the Christmas demand. While this behavior may show a positive effect on product availability (time-to-market) it may reduce the level of product maturity since final verification and fine-tuning activities are shortened or reduced. For example, a high number of immature production test cases (in terms of execution and tolerance limits) may cause more work in process and throughput losses compared with a fully verified and fine-tuned test setup. Since this may negatively affect the manufacturing ramp-up performance of the new product, a common managerial consequence is to find a trade-off - given strong demand for all products - between the limited availability of a new product versus the disturbance that is created in the factory. This trade-off also confronts the shift of many engineering resources to stabilize the new product ramp-up with the output loss of existing products that would use the same production line as the ramp-up product.

The combination of findings regarding supplier configuration and co-location (we found a strong relationship between supplier configuration and manufacturing ramp-up performance but no relationship between supplier co-location and manufacturing ramp-up performance) is intriguing. This finding suggests that the internal configuration of a supplier – the way how tool shops and their engineering capabilities are positioned within the manufacturing network of a supplier – is a more critical determinant for manufacturing ramp-up performance than co-location alone. In other words, product specific component supply in proximity to the tool shop and its engineering capability is more important than general supply proximity because “when it comes to knowledge, distance does matter” (Pisano and Shih 2009, p. 4). One explanation of this effect is based on the planning principle that prevails in Nokia during the ramp-up phase. During ramp-ups, factories execute a push plan based on sales forecasts as exact customer orders are not yet known. To avoid inefficiencies and reduce planning complexity, the push plans generally restrict the number of product variants (e.g., color, artwork). Consequently, the unsteady delivery of materials as a result of internal manufacturing difficulties at a supplier (e.g., molding equipment downtime due to assembly problems or quality issues on customer side that require tool modifications) has a more disruptive effect on manufacturing ramp-up performance than reduced responsiveness in terms of extended transportation lead times. While responsiveness and hence short lead times are critical under mass-production conditions (i.e., whenever the full variety of product variants can be ordered by customers), their effect is only of secondary importance during the ramp-up phase because the production program is still restricted to a decent amount of variants and already known in advance. As a result, this advocates a shift in the perspective of managers and researchers in the field of manufacturing strategy regarding the importance of co-location. If the positive impact of co-located suppliers on manufacturing ramp-up performance is in fact driven by the internal configuration of the suppliers and if the proximity between the tool shop capability and the associated part manufacturing location can minimize a performance penalty, the selection of lead suppliers should be based on their level of integration within the relevant capabilities – particularly in case of incomplete tool approvals and unstable part manufacturing conditions that prevail during the ramp-up phase.

Also, this study sheds light on the influence of sales forecast instabilities on manufacturing ramp-up performance. As consumer electronics products like all high-tech products experience fast-changing market conditions, it is imperative in this industry to respond quickly to these changes as our findings indicate that sales forecast instabilities have an significant effect on manufacturing ramp-up performance. As already pointed out in our Hypothesis, falling demand in particular is very likely to cause confusion on supplier side and to create a bullwhip effect in the supply chain. As a result, substantial fluctuations in the manufacturing and supply plans may occur even if the sales forecast varies only slightly over time. As Bozarth et al. (2009, p.81) note, "unstable production schedules will force manufacturers to either put in place planning and control systems that are capable of dealing with the complex interactions required to link production plans and execution activities, or experience unpredictable, non-linear impacts on lower-level production and material plans". This calls for awareness in management and sales teams in order to understand the effect of plan changes on overall manufacturing ramp-up performance and hence on product availability.

Finally, the joint consideration of supplier configuration and automation provides a plausible explanation for the finding that European plants show a lower average performance than their Asian counterparts – a finding that was already highlighted in chapter 3. The level of automation is strongly influenced by labor costs and since labor costs are generally lower in China and Korea than in Europe, it is more likely to find manual production lines in Asian plants. This argumentation is in line with our sample in which all Asian plants are equipped with manual lines. As a result, the European plants are much more exposed to the ramp-up challenges that are connected with higher levels of automation. Another explanation for the differences in performance related to plant location is based on the supply structure that prevails in Nokia. Compared to the situation in Europe, the percentage of supplier configurations in which tool shops and engineering capabilities are close by is higher in Asia since the majority of product specific part suppliers have their home base and engineering competence in China. European plants may also have co-located suppliers but these suppliers are connected with dedicated tool shops in China. This situation may cause a lasting damage on the European plants if sophisticated engineering and manufacturing capabilities that underpin innovation in products are geographically separated (Pisano and Shih 2009). Although these variables are structural in nature – i.e. not under direct control of the development team or factory management – there is still potential for managerial influence. Our results indicate that new product ramp-ups may benefit from lead plants that are not necessarily based in Asia but still operate in a highly manual and hence flexible manner and within supply networks that offer tightly interlinked engineering and manufacturing capabilities.

4.6 Conclusions

This chapter provides an empirical examination of the supply chain structure characteristics that are commonly thought to be related to manufacturing ramp-up performance. Our results highlight the fact that the internal organization of suppliers, the level of automation within a plant, the overall sales forecast stability and the time period in which a new product is ramped-up are important drivers of manufacturing ramp-up performance. Particularly the strong relationship between supplier configuration and manufacturing ramp-up performance enhances the exiting research by the introduction of a concept that is specific to a ramp-up context. Product specific component supply in proximity to the tool shop and its engineering capability is more important than supplier co-location. In addition, we argue that the differences in manufacturing ramp-up performance between European and Asian plants are primarily driven by the differences in automation (higher automation levels are more common in Europe as a result of labor cost pressures) and supply structure (the percentage of advantageous supplier configurations in which tool shops and engineering capabilities are close by is higher in Asia).

Because it is the main objective of the high-tech industry to achieve full-scale production and thereby time-to-volume targets as quickly as possible, our results suggest that managerial decisions regarding the selection of the lead factory are crucial for ramp-up success.

These findings trigger the need for future research to address potential weaknesses of the study and to explore further effects. First, there might be additional factors around the introduced supply-chain structure characteristics such as the organizational context and culture that may contribute to ramp-up performance. Further research could identify these factors and test their impact on manufacturing ramp-up performance within this framework. Also, a broader analysis including additional firms from the consumer electronics industry and the utilisation of a larger sample might reveal additional effects and enhance the generalizability of our findings specifically with regard to the effects of automation. While this study points out to the detrimental effects of automation, other studies highlight its benefits. Future research should explore the most effective and appropriate level of automation for both the ramp-up period and also the later phase of mass-production in different industry contexts.

Chapter 5

Conclusions

In this dissertation, we examined the ramp-up process of consumer electronics products – cell phones in particular – and we focused on the analysis of quantitative relationships between several influential characteristics, development lead time and ramp-up performance. We also investigated how these relationships change in the course of the ramp-up lifecycle and suggested potential explanations based on our knowledge and deep insights into the entire ramp-up process. In the following section we will summarize the results, insights and conclusions of our research studies more thoroughly. Additionally, we will provide detailed answers to the research questions that were posed in the introductory section of our study and demonstrate implications for the industrial practice – which is one of the main intentions of our research. Finally, we will discuss some ideas for future research.

5.1 The Impact of Product Complexity on Ramp-up Performance

In the introductory section we raised a number of research questions that are related to the determinants of product ramp-up performance. Our first question was stated as follows:

I. How can product complexity characteristics of consumer electronics devices, and specifically of cell phones, be modeled in quantitative terms?

The main objective of this question was to identify a set of complexity characteristics that we anticipated to be strong predictors of total product ramp-up performance. We were looking for characteristics that are already well described in the literature, theoretically rigorous and available for our data collection. Based on our literature review we find that across a wide range of disciplines –

including the physical sciences, engineering, and management – there are two basic approaches to define product complexity. The first one considers a product in functional terms and usually describes what the product is supposed to do rather than how it is designed and implemented. An example for this approach is the work of Griffin (1997). She operationalizes product complexity as the number of functions designed into a product. This applies across various industries and products but also has its limitations as a product function can be implemented into the physical structure of a product in various ways. For example, two cell phones might offer very similar functionalities but still vary considerably in their internal complexity. Consequently, we follow the second approach and consider products in physical terms and product complexity as a property of the product (Rodríguez-Toro et al. 2004). Due to our unique access to operational data we are able to measure the physical complexity – or as we call it hardware complexity – on the basis of Novak and Eppingers (2001) definition as (1) the total number of components = component count, (2) the number of signal networks across all electrical and electromechanical components = parts coupling, and (3) the percentage material value of new physical components in a complete cell phone = product novelty.

While this definition is consistent with the existing literature it ignores the growing importance of software which is often neglected in the available empirical studies (e.g., Clawson 1985, Langowitz 1987, Almgren 2000, Vandevelde and Van Dierdonck 2003, van der Merwe 2004, Berg 2007). However, in the case of consumer electronics products such as cell phones, functionality is steadily shifting from hardware to software. Hence, software increasingly affects the product development process. Just a few years ago, the cell phone market was dominated by single- and dual-band, single-mode cell phones that supported only few cellular bands and shared the same modulation schemes and protocols. In contrast, modern cell phone designs are much more complex, providing multiband, multimode cellular support, along with Bluetooth personal area networking, GPS-based positioning technology, WLAN for high-speed local-area data access, mobile digital TV for real-time viewing functionalities and user applications such as games, social networking clients and augmented reality. Also, software-based implementations have become more common as hardware release cycles are more expensive and inflexible (e.g., due to dependencies on external chip set suppliers and their schedules).

Previous research acknowledged that software complexity is multidimensional in nature (Banker et al. 1998, Zuse 1991) and proposed a variety of complexity measures. However, these measures vary on a small number of orthogonal dimensions (Banker et al. 1993, Munson and Koshgoftaar 1991) and incorporate common properties (Weyuker 1988). Hence, we calculate software complexity using a combination of indirect measures from the design specification and direct measures from the software code. In an approach that is similar to the definition of hardware complexity, we define software complexity as (1) the number of executable lines of code = SW code size, (2) the degree of software newness = SW novelty, and (3) the number of software errors = SW error count. SW error count plays a particular role in our definition of software complexity. First, early error assessment allows the development teams to predict the remaining development effort for the subsequent stages until ramp-up. Second, SW newness and SW code size do not sufficiently account for differences in the individual product configuration. Even a little amount of SW newness and small code size can for example lead to a disproportionate amount of development effort if the particular configuration results in a large number of errors due to interaction and side effects.

As we will show in the following sections this set of exactly quantifiable complexity characteristics contributes significantly to the explanation of manufacturing and total product ramp-up performance levels. At the same it time sheds light on different individual effects that help to enhance our understanding of the entire ramp-up process. This is the topic of our second research question:

II. How do product complexity characteristics interact with each other and subsequently influence manufacturing and total product ramp-up performance?

Our empirical analysis suggests a strong coupling between hardware and software characteristics which is consistent with the prevailing view that embedded systems like cell phones follow a hardware-software co-design approach. In addition, and based on our argumentation that most of the new innovations in cell-phones originate from new software features, we find a directional coupling from software to hardware complexity. In other words, functionality is more and more split into features that can be implemented via software as hardware release cycles are slower and inflexible. Thus, software is actually determining the hardware characteristics. This is a unique feature of cell phones and stands in contrast to other electronic products that differ from this co-design approach, hence they may either not show this coupling (e.g., desktop PCs) or even show a reversed coupling from hardware to software (e.g., ultra-low cost devices such as toys in which the hardware configuration determines the costs and thus also the feasible software functionalities).

In a next step, we analyzed the individual contributions of these complexity characteristics on manufacturing ramp-up performance which we defined as a combination of final yield and effective utilization. While we find that final yield is dependent on product specific component count (i.e., a complexity characteristic that is likely to increase opportunities for failure during production) we find effective utilization to be dependent on product specific component count and parts coupling. Interestingly, the strong impact of manufacturing ramp-up performance on total product ramp-up performance is due to effective utilization and not due to final yield. In their pursuit to improve total product ramp-up performance, managers should therefore focus on effective utilization instead of final yield. This suggests that yield losses can be compensated during the ramp-up phase (i.e., on behalf of sufficient repair capacity) while drops in effective utilization due to unscheduled downtime, setup changes or reduced speed – which depends on product specific component count and parts couplings as we mentioned above - cannot be absorbed by any repair activity and hence has a direct and immediate impact on manufacturing ramp-up performance. As an example, the inability of sourcing teams to provide the right material on time and in the required quantity is a common disturbance factor for effective utilization. That is because material management is a very complex process and the related factors like forecasting, supplier coordination and engineering change handling increase with the number of components that have to be managed. Another commonly found obstacle for effective utilization is related to the applied production test systems. These systems are among the most complex within the manufacturing line and their stability and robustness depends on the required level of product specific adaptation and on the specified test plan complexity which is a function of product specific component count and their couplings. For this reason, products with numerous components and complex parts couplings are more likely to cause disturbances regarding effective utilization which results in difficulties for the manufacturing ramp-up performance and ultimately in a lower total product ramp-up performance since the generic part of a cell phone – produced by the manufacturing system – is a precondition for the subsequent final configuration activity as mentioned in section 1.2. Cell phones are manufactured with delayed customization (i.e., postponement), thus the final customization does not take place until real customer orders are known. As a result, manufacturing ramp-up performance represents how well the generic parts of a cell phone is manufactured or aggregate production plans are met. Poor manufacturing ramp-up performance will thus result in significant downstream problems since final configuration activities cannot take place as planned, customer shipments are delayed and ultimately total product ramp-up performance will suffer.

While manufacturing ramp-up performance – with effective utilization as a key characteristic – turns out to be the strongest predictor of total product ramp-up performance, we find that the novelty aspects of both software and hardware are also significant drivers of total product ramp-up performance. As expected, product novelty has a negative effect on total product ramp-up performance since novel designs increase the number of uncertainties and issues that development teams, manufacturing teams, suppliers and even customers have to cope with. In response, the achievement of planned performance levels requires more learning. Another observation is the fact that products with a large share of product novelty are particularly slow at the beginning of the ramp-up period which forces the ramp-up teams to achieve a disproportionately high increase in output towards the end of the ramp-up period. While cumulative levels of manufacturing output may be on track at the end of the ramp-up period, final configuration activities are often behind schedule due to the delayed arrival of products at the customization and distribution stage.

Surprisingly, software novelty has a positive effect on total product ramp-up performance. As we pointed out earlier, software schedules become increasingly unpredictable and late schedule slips are increasingly likely due to the ongoing growth with reference to software content and complexity. Firms may respond to potential ramp-up delays due to a lack of software readiness with a gradual start of production since in most cases the hardware components are already available and prepared for production in such cases. Despite the rising inventory levels for semi-finished products, such an approach can be helpful to prepare production and material supply for the rescheduled ramp-up. As soon as the software release is ready and approved for production only a simple re-programming step is required and the product buffers are immediately available. This allows for higher output levels during the initial ramp-up phase.

5.2 How does Development Lead Time affect Performance over the Ramp-up Lifecycle

After having described the relevant product complexity and manufacturing characteristics associated with ramp-up performance and after offering an enhanced understanding of their effects we can now turn to the next question and analyze how these relationships change over the ramp-up lifecycle. In addition, we extend our consideration by including development lead time as a new variable in order to study not only time-to-volume but also time-to-market determinants. This leads us to our third research question:

III. What are the interrelationships between product characteristics (product complexity), product development process characteristics (development lead time) and manufacturing ramp-up performance over the course of the ramp-up lifecycle?

We addressed this question in chapter 3 by aggregating the previously specified characteristics into formative constructs in order to use PLS path modeling. This means we integrated component count (separated into product specific component count and common component count), parts coupling and product novelty into a hardware complexity construct and arranged the software related characteristics (SW code size, SW novelty, SW error count) within a software complexity construct. In addition, we included product development lead time as an additional construct that is made up by the different product development phase durations and linked all constructs to the manufacturing ramp-up performance construct represented by effective utilization. The key findings from this advanced approach confirm our earlier results that were based on a series of OLS models but in addition, they also provide insights into the determinants of product development lead time.

Most noticeable, our PLS results suggest software complexity to be the dominant driver for development lead time in cell phone projects. This result is in line with our Hypothesis that functionality steadily shifts from hardware to software and hence increases the scale and level of uncertainty in the software design task as well as the tendency to fix hardware errors via software solutions. In addition, we observe a trend that hardware becomes a commodity that is available from different sources. This, in turn, calls for the involvement of purchasing managers with a focus on material cost. As a result, there are examples in which development teams were forced to adapt the software code to second source components and slower but more cost efficient processors – activities that typically tend to have a negative correlation with schedule performance. The managerial implication of this finding is that time-to-market improvements are more likely if product development managers focus on diminishing the complexity of the software design tasks instead of decreasing hardware complexity by using fewer and less novel components. In highly competitive markets where the market imperatives entail the implementation of higher levels of software complexity, managers need to understand the potential impact of their product design decisions and the potential of software engineering practices (e.g. software postponement) to accommodate to such risks.

Having identified software complexity as the main determinant of development lead time, we subsequently find a detrimental effect of compressed development lead times on manufacturing ramp-up performance. Shorter development lead times mean that the various project activities have to be executed faster than normal, which makes it harder for project managers to predict activity outcomes and thus more difficult to achieve on-time performance (Swink 2003). In projects with highly compressed schedules we additionally experienced fewer design-build-test cycles and less time for evaluation activities between these cycles. These circumstances often cumulated in late fine-tuning activities and hence in discontinuous output during the ramp-up phase. Also, product development managers are tempted to shorten the development lead time in order to profit from special events (e.g., trade shows) or high peak sales periods (e.g., Christmas). While the inflow of revenues depends on time-to-market performance, firms must be careful not to over-accelerate the development lead time because customer relations can be negatively affected if the required ramp-up performance levels (i.e., output levels according to plan) cannot be accomplished. Managers need to be aware of the tradeoff between speed of development and sustained ramp-up performance as suggested by our results in order to assign the most suitable launch timing strategy.

In addition to the already mentioned insights we also find slip – defined as the time delay between the planned and actual ramp-up start – to have a positive effect on manufacturing ramp-up performance. This stunning effect suggests that schedule slips – frequently caused by errors that are detected in the final acceptance phase but fixed in software due to the short release cycles – allow for the gradual start of production and the buildup of semi-finished product buffers ahead of the rescheduled ramp-up. This allows for the execution of additional engineering trials to fine-tune the manufacturing process, review the supplied material quality and the consumption of created product buffers at the start of the full scale ramp-up phase. However, the practical constraint of this approach is the fact that only early product availability is improved while development lead time on the other hand is not affected.

Finally, we explored the behavior of these relationships over the entire ramp-up lifecycle in order to illustrate the dynamic nature of the ramp-up process. In a first step, we applied our model to a relatively short ramp-up period of four weeks (i.e., manufacturing ramp-up performance is calculated over the first four weeks of the ramp-up execution phase) and hence were able to observe that the very dynamic and chaotic ramp-up start can only be partially captured by our model. However, this situation changes if we increase the examined time period to eight weeks. Predictive relevance clearly increases and slip turns out to be a significant positive predictor of manufacturing ramp-up performance – for which we have provided an explanation above. However, this positive effect of slip fades out rather quickly if the considered time horizon is further increased. In other words, the effect of slip quickly diminishes after the product buffers created during the initial delay are used up. Over a period of 12 weeks we gained the same results that have already been illustrated. If we increase the examined ramp-up period beyond the 12 week horizon we find that ramp-up specific difficulties diminish while factors related to mass volume production start to appear.

If we consider the complexity characteristics and their impact on manufacturing ramp-up performance only, we find a distinctly different pattern between them. Hardware characteristics seem to be a permanent source of difficulty over the entire life cycle which suggests that the problem solving cycles related to hardware components are slow and cumbersome (i.e., there is typically substantial pipeline inventory that needs to be used up before component changes or updates can be introduced). Software complexity on the other hand shows a more volatile pattern. This may be the result of rather quick software and variant creation release cycles that allow for rather quick reactions to new problems and occurring errors.

5.3 Uncovering Plant Specific Differences during New Product Ramp-ups

We finally turn to our last research question in which we analyze additional characteristics that are supposed to affect manufacturing ramp-up performance in order to gain additional insights into the entire ramp-up process:

IV. *What supply-chain structure characteristics uncover plant specific effects in the context of manufacturing ramp-up performance*

In summary, the empirical results in chapter 4 suggest that the level of automation within a plant and the internal organization of key suppliers (i.e., suppliers that are responsible for product specific parts) – as well as the ramp-up timing and overall sales forecast stability – are significant drivers of manufacturing ramp-up performance.

Although automated systems are often considered to be highly effective and efficient in high volume production, our results suggest that the benefits of automation are rather limited in a ramp-up context due to the intrinsic inflexibility of most automated systems. We observed that even small variations in the quality (e.g., dimensional variations) or packaging of parts may interrupt the production flow of automated systems (i.e., grippers, fixtures, assembly systems, robots, transportation systems) and hence result in line stops or reduced output. For example, human operators can easily deal with slight variations in part dimensions by adapting the assembly procedure, the usage of auxiliary tools or by adapting the assembly force. Automated grippers or assembly robots on the other hand require re-adjustments, gripper modifications or program changes that result in extended down time. The fact that the configuration and installation process of most automated systems is performed with pre-ramp-up material that does not represent the full range of variation commonly found in mass-production is a possible explanation for this effect. The results are laborious fine-tuning activities – mainly during the ramp-up phase – that have a direct effect on downtime and hence on manufacturing ramp-up performance. Manual systems (i.e., assembly jigs and fixtures) on the other hand are simple to install and easy to adapt. In case of damage it is also easier to repair or duplicate them. In addition, manual systems are already available during the prototyping phase (as a result of their simplicity compared to complex automated solutions that require longer development and production lead times), therefore they can benefit from several improvement rounds during the development phase.

Most noticeable is our finding regarding the significance of supplier configuration compared to supplier co-location. In a ramp-up context, the way how tool shops and their engineering capabilities are positioned within the manufacturing network of a supplier seem to be a more critical determinant of manufacturing ramp-up performance than supply proximity. This effect suggests that the unsteady delivery of product specific material (i.e., as a result of internal manufacturing difficulties of key suppliers) has a more disruptive effect on manufacturing ramp-up performance than reduced responsiveness caused by longer transportation lead times. Internal manufacturing difficulties (e.g. molding equipment downtime that allows for part quality improvements) may benefit from co-located engineering teams in terms of shorter feedback loops and problem solving cycles. Additionally, the planning principle that prevails in Nokia during the ramp-up phase is based on a pre-determined push plan in which product variants are restricted and production volumes are known in advance. Hence, responsiveness and short supply loops may be more critical after the ramp-up phase is over (i.e., mass production conditions) and customers are actually able to order the full product spectrum. Managers should thus consider the performance penalty differences that may occur under unstable part manufacturing conditions as they are in fact driven by the internal configuration of the involved suppliers.

Considering the effects of automation and supplier configuration together provides a plausible explanation for differences in manufacturing ramp-up performance between European and Asian plants – an observation which we already made in our earlier models. As automation is less common in our Asian plants due to the lower average labor cost, we expect European plants to be more exposed to the challenges described above. In addition, and since the majority of Nokia’s key suppliers have their home base in China, the percentage of key suppliers that have their engineering teams, tool shops and manufacturing lines in close proximity is far higher in Asia. While the European manufacturing plants in our sample have co-located suppliers as well, we observe that most of their tool shops are primarily located in China. These factors are structural in nature – i.e. not under direct control of product development managers – but still provide guidance in terms of the lead factory selection. Manufacturing ramp-up performance may benefit from highly manual and hence flexible manufacturing plants that are embedded in a supply network in which suppliers have tightly interlinked engineering and manufacturing capabilities in order to respond quickly to unsteady part delivery conditions.

5.4 Implications

Now that we have listed the key conclusions from our study, we want to complete this discussion with a look at some of the implications around software complexity, ramp-up performance and development lead time.

We believe that the separation of complexity into hardware and software characteristics provides a highly effective approach to guide management decisions during the phase of new product development. Products that are expected to imply a high degree of hardware complexity may for example significantly gain from early manufacturing involvement (Swink 1999), from DfM activities (Susman and Dean 1992) that focus on lowering product novelty and product specific component count and from a careful selection of the lead factory with regard to the best possible product-factory fit (Langowitz 1988). Our findings from Chapter 4 that emphasize the structure of the supply chain along with additional factors such as automation and supplier configuration are closely related to the topic of product-factory fit. Concerning automation, we believe that the common principle that governs success with reference to ramp-up performance is related to the appropriate levels of automation (Säfsten et al. 2007) and to the application of successful strategies for automation system integration (Liao and Tu 2008). Our observations indicate that profound automation system integration and the utilization of robust automation systems (Kuhn et al. 2002) that tolerate minor part variations are required to achieve a positive effect from manufacturing system automation on manufacturing ramp-up performance. The same applies for the concept of supplier configurations that enable close interactions between process engineering and manufacturing in order to achieve superior ramp-up performance. We consider this factor not as a unique characteristic of the consumer electronics industry but as a subset of cross-functional integration strategies (Wheelwright and Clark 1992).

On the other hand, the above-mentioned approaches will most likely be rather inefficient in products with a high degree of software complexity where other approaches such as proactive variant management and software postponement may prove useful. Particularly in consumer electronics where the influence and importance of software content has increased substantially in the past years, product development managers need to appreciate the central importance of software for these products and its effect on the hardware configuration, development lead time and late schedule slips. While schedule slips that result from software delays or development lead time extensions (e.g., needed to accommodate for software feature implementations) may be used productively within the manufacturing system (e.g., to fine tune the manufacturing system or to create semi-finished product buffers) and at suppliers, their overall effect on time-to-market performance and ultimately on profits is considerably negative. The same implications likely apply for many other products or product categories, including hi-fi systems, cameras, flat screens and tablet computers. Hence, effective software engineering with a strong focus on schedule adherence became a crucial capability for the successful and timely market launch of new consumer electronics products.

In response to the challenges observed in the development of embedded systems there seems to be a trend among the manufacturers of modern cell phones and smartphones to abandon the embedded systems approach with its tight coupling between hardware and software elements and to switch to a software platform strategy. Today, products tend to be designed and delivered based on an in-house developed hardware platform and on an independent software platform that is provided by a third party supplier. In consequence, this disconnection of hardware and software development reduces the amount of product specific software development efforts and offers greater flexibility for updates at later stages of the product lifecycle. We are confident that this trend will spread into other industries as well, particularly into industries that also combine innovation speed and cost driven mass-market characteristics with high demands on usability and quality. Various consumer electronics products share similar product characteristics and even the automobile industry starts to show increasingly comparable properties as a result of the user benefits that can be provided with electronic enhancements (e.g., parking and driver assistant systems or multimedia systems). Compared to the traditional embedded systems approach (that leads to a fixed hardware-software architecture), a shift towards the integration of third party software platforms may have significant consequences for future business models, for own innovative contributions and for the required software engineering competences. For example, the scattering of functionalities into apps (i.e., user downloadable software applications) forces companies to redeploy their development resources. Software resources could be drawn away from the development of operating systems and concentrated in the development of innovative applications. A positive side effect of this shift is related to the increased planning flexibility of project managers as the start of production can be planned and organized virtually independent of the app development.

Another managerial implication arises from our approach to consider ramp-up performance in terms of manufacturing ramp-up performance and total product ramp-up performance. This dual concept is justified by the fact that cell phones – like several other consumer electronics products – are manufactured with delayed customization (i.e., postponement). Thus, the final customization does not take place until real customer orders are known. As a result, manufacturing ramp-up performance represents how well the generic parts of a cell phone are manufactured according to a predefined ramp-up plan. Total product ramp-up performance instead measures how well these generic parts are converted into customer specific products, then distributed and invoiced. Based on our findings, these performance measures do not only highlight different aspects of the ramp-up process but also support managerial actions at different areas. Since manufacturing ramp-up performance was identified to be the strongest predictor of total product ramp-up performance, ramp-up managers in the factories should focus primarily on product availability (i.e., effective utilization) and secondarily mitigate all issues that arise from product novelty characteristics (refer to chapter 2). In consequence, stabilizing product availability requires managerial support by the program management team regarding those influential characteristics that we identified in chapters 3 and 4.

Finally, and based on our results and observations, we propose some recommendations in order to strengthen ramp-up performance, although they are partly beyond the scope of our formal empirical analysis. First and foremost, managers need to accept and deal with the tradeoff between product maturity (that may arise from an increased amount of design-build-test cycles as pointed out in chapter 3) and manufacturing ramp-up performance. Early product availability can be improved in the short term if management squeezes product development lead time (e.g., via reducing design-build-test cycles or via shortening the time between cycles). In the mid-term, however, we have experienced considerable drops in delivery performance as a result of the many engineering changes that need to be introduced in the product, the manufacturing system and at suppliers in order to enable reliable high volume production. Additionally, and particularly in connection with low product maturity levels, gradual production ahead of the actual ramp-up start enables ramp-up teams and suppliers to gain experience in production execution and to fine tune part quality levels that both foster throughput and ultimately ramp-up performance. We believe that these findings are neither unique to the cell phone industry, nor to the wider consumer electronics industry.

Second, the results of our study suggest that it may be recommendable to allocate excess manufacturing capacity for selected key products. A finding that is in contrast to the still prevailing paradigm to focus on high capacity utilization levels. Allocating excess capacity was found to reduce delivery risks which we believe to be more critical in a ramp-up context (as delivery inabilities directly affect customers) than internal manufacturing costs. This strategy has to be an integral part of the business case calculation and the incentive plan for product development teams in order to identify the most appropriate level of excess capacity.

Third, the incentive schemes for product development teams in the last development phase should not solely be based on development lead time criteria but on a reasonable combination of development lead time and ramp-up performance. In response, ramp-up teams will still focus on early product availability (time-to-market) – which is crucial to fetch premium prices and achieve profits – but also on delivery performance – which is a crucial factor for customer relations and potential long term agreements with customers.

5.5 Future Research Directions

In this section, we discuss some ideas for future research by going through the different chapters of this dissertation.

Although we have attempted to build a comprehensive model that captures the key determinants of manufacturing and total product ramp-up performance in chapter 2, we also note that further research could still address some limitations of our model. First, our model explains only around half of the variance in manufacturing and total product ramp-up performance but there are additional factors that may be relevant and contribute to ramp-up performance. As summarized in Table 1, there are various factors that are proposed by the existing literature, ranging from cultural factors to organizational aspects. Future research could attempt to select the most promising factors in order to quantify them in detail and to analyze their contribution in the model provided within this thesis. Consumer electronics products are manufactured on a global scale. The insights regarding differences in ramp-up performance that are caused by cultural factors such as the ones proposed by Hofstede (2001) might be particularly relevant in the context of lead factory selection and plant location.

Next, and as mentioned in chapter 2 and 3, our conclusions are based on a limited number of real life cases that were carried out in a single firm. A wider analysis including different firms from the consumer electronics industry or the automotive industry – from which most of the existing ramp-up literature stems from – and the application of a larger sample size might reveal additional effects and enhance the generizability of our results. The automotive industry in particular might benefit from our models as modern automobiles start to share various characteristics with consumer electronics products especially with regard to the application of embedded systems technology. Such an extension might also reveal how the existing model parameters change under different product development cycles. We would expect to find a stronger relationship between product complexity and manufacturing ramp-up performance in industries that introduce few but progressive product updates and a weaker relationship in industries that introduce rather small but frequent updates.

Also, and as addressed in chapter 4, there seems to be a detrimental effect of automation on manufacturing ramp-up performance although there are a number of studies that highlight the advantages of automation. Further studies should explore this relationship in more detail by taking different industry contexts into account and a broader view on production technology in general. Hence, future studies may be able to define the most effective and appropriate level of production technology complexity for the ramp-up phase that is also appropriate to support later mass-production conditions.

Finally, different methodologies with a focus on analytical modeling may enhance our results and increase the scope of their applicability. For example, we have identified a relation between schedule performance and manufacturing ramp-up performance that could be assessed in more detail with formal models. The results of such an approach may be helpful to guide managerial action but also lead to new ways of project and ramp-up planning. Also, our results suggest that being more restrictive with initial sales volume plans increases total product ramp-up performance but at the expense of total output, cost and thus profit. Analytical models could be used to find the optimal balance between the amount of reserved material and capacity for a new product and the volume plan that should be confirmed to customers based on the complexity of the new product. The insights gained from such models could serve as an important source of input for risk assessments and incentive schemes.

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Summary

New product development (NPD) is particularly challenging in the high-technology sector, increasingly characterized by shortening product lifecycles, rising market fragmentation, and rapid technological changes (Bowersox et al. 1999, Mallick and Schroeder 2005, Wildemann 2007). If firms want to succeed in this environment, short development lead times and efficient ramp-ups are invaluable for several reasons. First, the faster a company can ramp-up production of a new product, the more quickly it can begin to earn significant revenues from the new product and recoup its development investments (Pisano and Wheelwright 1995). Secondly, fast ramp-ups enable firms to profit from early market opportunities, set technology standards and accumulate experience with volume production. Finally, scarce product development and manufacturing engineering resources can be released to support subsequent product development projects instead of solving production problems.

Yet many companies fail to meet their new product introduction targets regarding time-to-market and time-to-volume. Schuh et al. (2005) show that 47% of automotive new product ramp-ups were neither technically nor economically successful. Kuhn et al. (2002) indicate that not a single company in their study claimed its production ramp-up was under control. Thus, the ramp-up phase remains a major challenge, even as it provides a significant opportunity for competitive advantages. Despite multiple studies that have identified a vast number of influential factors, we know very little about the quantitative and causal relationships between these factors and ramp-up performance. Krishnan and Ulrich (2001) argue that essentially no work has investigated the relationship between the rate of production ramp-up and product design decisions.

This research project addresses the above mentioned limitation with a set of three research studies that are based on operational data from Nokia, a mobile device and service company headquartered in Espoo, Finland. Based on the individual cell phone designed and manufactured by Nokia as the unit of analysis, we investigate four research questions: (1) How can product characteristics (i.e., product complexity) of consumer electronics devices, and specifically of cell phones, be modeled in quantitative terms? (2) How do product complexity characteristics interact with each other and subsequently influence manufacturing and total product ramp-up performance? (3) What are the interrelationships between product complexity characteristics, product development process characteristics (i.e., development lead time) and manufacturing ramp-up performance over the course of the ramp-up lifecycle and (4) What supply-chain structure characteristics uncover plant specific effects in the context of manufacturing ramp-up performance? In order to address these questions, we introduce a conceptual framework in an introductory paper (Pufall et al. 2007) that is based on an

extensive literature review. This framework summarizes the key factors that influence ramp-up performance and serves as our guiding principle for the subsequent empirical studies.

Based on this framework, our first study uses a set of multiple linear regression (MLR) models that relate quantitative product complexity characteristics – represented by software and hardware complexity variables – and manufacturing ramp-up performance variables to total product ramp-up performance. We demonstrate that new cell phone features are gradually shifting towards software based implementations that can be implemented on generic hardware. Beyond the fact that software characteristics are gaining importance in driving hardware complexity, we also find that certain hardware characteristics (i.e., product specific component count and parts coupling) have a significant impact on the performance of the manufacturing system in terms of final yield and effective utilization. We also find that effective utilization together with the novelty aspects of software and hardware complexity (i.e., SW novelty and product novelty) are the key determinants of total product ramp-up performance.

Our second study uses a partial least squares (PLS) path modeling approach to examine the impact of additional variables and different time horizons on manufacturing ramp-up performance. Compared to MLR and covariance based structural equation modeling approaches (e.g., LISREL), PLS is particularly well suited for studies using operational data and if the primary research objective is the simultaneous maximization of explained variance in all endogenous constructs (i.e., prediction) instead of achieving model "fit". An additional result of this study is the finding that development lead time is an important predictor for manufacturing ramp-up performance. While longer development lead times facilitate higher product maturity and thus sustained manufacturing ramp-up performance, later market introductions of new products imply a negative impact on revenue inflows. Additionally, our results suggest that late schedule slips, although disastrous for customer relations in which due dates are crucial, provide the opportunity to build up (semi-finished) product buffers which in turn increase the initial manufacturing ramp-up performance.

Finally, our third study highlights that the internal organization of suppliers, the level of automation within a plant and the time period in which a new product is ramped-up are also important drivers of manufacturing ramp-up performance. Because it is the main objective of the high-tech industry to achieve full-scale production and thereby time-to-volume targets as quickly as possible, our results suggest that the selection of the ramp-up factory is a crucial factor for ramp-up success.

In summary, our study contributes to the field of operations management by demonstrating the relevant characteristics of product complexity, development lead time and manufacturing that are associated with manufacturing and total product ramp-up performance and by offering a substantially enhanced and more detailed understanding of the entire ramp-up process.

About the Author

Andreas Pufall was born in Ulm, Germany, on May 06, 1969. After completing his pre-university education at the "Ferdinand-von-Steinbeis" College in Ulm, Germany, he studied Precision Mechanical Engineering at the "Fachhochschule für Technik" in Esslingen, Germany. In 1994 he graduaded as Dipl.-Ing. (FH) in Engineering among the top of his class. Between 1995 and 1999 he worked as a Production Engineer at the Kodak AG in Stuttgart before joining the Nokia GmbH in Ulm in the position of an Operations Project Manager. In this position he served as the interface between the product development teams in Ulm and the global factory network of Nokia. In addition, he was specifically responsible for eight new product ramp-ups. While he was employed at Nokia he also completed an MBA study at the University of Lincoln, England. After the successful completion of his MBA studies he started a research project at the Eindhoven University of Technology, The Netherlands under the supervision of Jan Fransoo, Ton de Kok and Ad de Jong. The results of this project are presented in this dissertation.

Appendix

Appendix-A

Appendix-A1. Descriptive statistics and correlations (Pearson) between variables for chapter 2.

		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
1.	SW novelty	1.00															
2.	SW code size	0.14	1.00														
3.	SW error count	0.36	0.08	1.00													
4.	common component count	0.31	0.18	0.34	1.00												
5.	product specific component count	0.28	0.66	0.28	0.36	1.00											
6.	parts coupling	0.22	0.60	0.40	0.62	0.58	1.00										
7.	product novelty	0.83	0.12	0.54	0.25	0.22	0.24	1.00									
8.	final yield	-0.52	-0.32	-0.51	-0.46	-0.56	-0.48	-0.49	1.00								
9.	effective utilization	-0.26	-0.23	-0.53	-0.32	-0.42	-0.52	-0.34	0.50	1.00							
10.	linear trend	-0.48	0.47	0.03	-0.13	0.31	0.34	-0.29	0.12	-0.03	1.00						
11.	plant age	-0.18	-0.28	-0.09	-0.36	-0.39	-0.35	-0.24	0.15	0.19	0.09	1.00					
12.	plant location	-0.46	0.25	-0.31	-0.36	0.08	-0.06	-0.29	0.41	0.34	0.53	-0.12	1.00				
13.	plant ownership	0.15	0.09	-0.11	-0.21	-0.05	-0.09	0.12	0.07	0.11	0.03	0.34	0.33	1.00			
14.	excess capacity	0.01	0.36	0.37	0.19	0.43	0.52	0.03	-0.37	-0.39	0.43	-0.15	-0.09	-0.18	1.00		
15.	sales forecast change	-0.01	-0.13	-0.09	0.08	-0.24	-0.09	-0.09	0.16	0.21	-0.44	0.09	-0.09	-0.04	-0.34	1.00	
16.	total product ramp-up performance	-0.14	-0.08	-0.07	-0.22	-0.13	-0.26	-0.16	0.16	0.58	0.23	0.10	0.17	-0.14	0.23	-0.11	1.00
Mean		51.48	6.2M	1000.00	350.35	149.70	555.43	0.16	0.92	0.77	624.02	6.62	0.72	0.87	0.22	1.07	0.85
S.D.		61.50	4.0M	2185.00	58.21	59.45	134.34	0.19	0.04	0.20	295.92	3.08	0.46	0.34	0.21	0.37	0.28
Minimum		0	0.7M	-1214	216	52	287	0.00	0.83	0.38	0	2.8	0	0	-0.14	0.36	0.33
Maximum		242	20.2M	7215	457	294	842	0.73	0.98	1.18	1147	12.5	1	1	0.79	1.91	1.44

Appendix-A2. Unstandardized regression results of the findings presented in Table 5.

	Dependent variables			
	common component count	*product specific component count*	*parts coupling*	*product novelty*
Predictor variables				
Constant	313.72 (16.91)	74.32 (13.42)	386.31 (30.65)	-0.007 (0.029)
SW novelty	0.194 (0.143)	0.119 (0.114)	0.044 (0.259)	0.0022 *** (0.00025)
SW code size	0.0000019 (0.0000021)	0.000009 *** (0.0000016)	0.000019 *** (0.0000037)	-0.000 (0.000)
SW error count	0.0068 * (0.004)	0.00517 (0.0032)	0.022 *** (0.0073)	0.000024 *** (0.000007)
Full model (*F*- and *p*- statistics)	2.94 [0.044]	14.08 [0.000]	13.48 [0.000]	44.47 [0.000]
R-Sq(adj)	11.50%	46.60%	45.40%	74.30%

Notes: N = 46, values in parentheses are standard errors, values in brackets are p-values, *** p ≤ .01, ** *p* ≤ .05, * *p* ≤ .10, two-tailed tests.

Appendix-A3. Unstandardized regression results of the findings presented in Table 6.

	Dependent variables					
	final yield			*effective utilization*		
Predictor variables						
Constant	0.962 *** (0.009)	1.008 *** (0.025)	0.990 *** (0.036)	1.227 (0.113)	2.358 *** (0.281)	2.079 *** (0.400)
SW novelty	-0.00021 ** (0.00007)	-0.00016 (0.00012)	0.00015 (0.00016)	-0.0014 (0.001)	-0.0023 (0.0014)	0.0011 (0.0018)
SW code size	-0.000 ** (0.000)	0.000 (0.000)	-0.000 (0.000)	-0.00000003 ** (0.00000001)	0.000 (0.000)	0.000 (0.000)
SW error count	-0.000006 ** (0.000002)	-0.000004 (0.0000024)	-0.0000024 (0.0000025)	-0.00003 (0.000027)	-0.0000075 (0.000027)	0.0000038 (0.000027)
common component count		-0.000089 (0.000095)	-0.000066 (0.0001)		-0.0015 (0.0011)	-0.00069 (0.0011)
product specific component count		-0.00022 ** (0.000098)	-0.00031 *** (0.000098)		-0.0021 * (0.0011)	-0.0025 ** (0.0011)
parts coupling		-0.0000058 (0.000052)	-0.00003 (0.000051)		-0.00096 * (0.00058)	-0.0014 ** (0.00057)
product novelty		-0.0021 (0.044)	-0.058 (0.045)		0.685 (0.490)	0.165 (0.501)
Control variables						
linear trend			0.00005 * (0.000027)			0.00038 (0.0003)
plant age			-0.003 (0.002)			0.007 (0.023)
plant location			0.013 (0.015)			0.294 * (0.170)
plant ownership			0.004 (0.016)			-0.184 (0.174)
sales forecast change			0.015 (0.011)			-0.150 (0.117)
Full model (*F*- and *p*- statistics)	11.18 [0.000]	6.49 [0.000]	5.24 [0.000]	4.33 [0.000]	6.56 [0.000]	5.48 [0.000]
R-Sq(adj)	40.4%	46.1%	53.0%	18.2%	46.4%	54.4%

Notes: N = 46, values in parentheses are standard errors, values in brackets are *p*-values, *** *p* ≤ .01, ** *p* ≤ .05, * *p* ≤ .10, two-tailed tests.

Appendix-A4. Unstandardized regression results of the findings presented in Table 7.

	Dependent variable		
	total product ramp-up performance		
Predictor variables			
Constant	1.276 *** (0.272)	0.473 (1.429)	0.976 (1.448)
SW novelty	0.00037 (0.0014)	0.002 (0.001)	0.003 ** (0.001)
SW code size	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
SW error count	0.000024 (0.000026)	0.000026 (0.000022)	0.0000056 (0.00002)
common component count	-0.00026 (0.0010)	0.00096 (0.00086)	0.0013 (0.00082)
product specific component count	-0.00022 (0.0011)	0.00056 (0.0009)	-0.0005 (0.00093)
parts coupling	-0.0007 (0.00056)	-0.00011 (0.00046)	-0.00066 (0.00045)
product novelty	-0.359 (0.475)	-0.785 ** (0.387)	-0.736 * (0.374)
final yield		-0.653 (1.410)	-1.157 (1.403)
effective utilization		0.620 *** (0.126)	0.544 *** (0.123)
Control variables			
linear trend			0.0003 (0.00025)
plant age			-0.003 (0.017)
plant location			0.124 (0.132)
plant owenership			-0.177 (0.125)
sales forecast change			0.151 * (0.088)
excess capacity			0.555 *** (0.198)
Full model (*F*- and *p*- statistics)	0.66 [0.706]	3.52 [0.003]	4.29 [0.000]
R-Sq(adj)	0.0%	33.5%	52.3%

Notes: N = 46, values in parentheses are standard errors, values in brackets are *p*-values, *** $p \leq .01$, ** $p \leq .05$, * $p \leq .10$, two-tailed tests.

Appendix-B

Appendix-B1. Descriptive statistics and correlations (Pearson) between variables for chapter 3.

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
1. M0toM1	1.00																	
2. M1toM2	0.14	1.00																
3. M2toM3	0.24	0.23	1.00															
4. common component count	-0.10	0.19	0.33	1.00														
5. product specific component count	0.31	0.07	0.08	0.36	1.00													
6. parts coupling	0.24	0.07	0.22	0.62	0.58	1.00												
7. product novelty	0.18	0.55	0.42	0.25	0.22	0.24	1.00											
8. SW novelty	0.12	0.65	0.50	0.31	0.28	0.22	0.83	1.00										
9. SW error count	0.33	0.26	0.41	0.34	0.28	0.40	0.54	0.36	1.00									
10. SW code size	0.44	0.11	0.06	0.18	0.66	0.60	0.12	0.14	0.08	1.00								
11. effective utilization	-0.08	0.00	-0.12	-0.32	-0.42	-0.52	-0.34	-0.26	-0.53	-0.23	1.00							
12. linear trend	0.33	-0.42	-0.30	-0.13	0.31	0.34	-0.29	-0.48	0.03	0.47	-0.03	1.00						
13. planned development lead time	0.73	0.58	0.47	0.07	0.12	0.19	0.37	0.38	0.43	0.19	-0.07	-0.10	1.00					
14. slip	0.05	0.21	0.61	0.16	0.15	0.05	0.49	0.48	0.28	0.08	0.00	-0.08	0.09	1.00				
15. sales forecast change	-0.15	0.15	0.01	0.08	-0.24	-0.09	-0.09	-0.01	-0.09	-0.13	0.21	-0.44	0.02	-0.13	1.00			
16. plant age	0.04	-0.10	-0.13	-0.36	-0.39	-0.35	-0.24	-0.18	-0.09	-0.28	0.19	0.09	0.03	-0.07	0.09	1.00		
17. production technology novelty	0.06	0.19	0.02	0.21	0.04	0.01	0.20	0.05	0.23	-0.14	-0.14	-0.12	0.20	0.16	0.17	0.10	1.00	
18. plant location	0.20	-0.29	-0.31	-0.36	0.08	-0.06	-0.29	-0.46	-0.31	0.25	0.34	0.53	-0.10	-0.17	-0.09	-0.12	-0.15	1.00
Mean	84.80	106.83	52.67	350.35	149.70	555.43	0.16	51.48	1000.00	6.2M	0.77	624.02	218.02	7.07	1.07	6.62	0.35	0.72
S.D.	56.34	42.41	23.58	58.21	59.45	134.34	0.19	61.50	2185.40	4.0M	0.20	295.92	64.08	16.36	0.37	3.08	0.48	0.46
Minimum	1.00	20.00	1.00	216.00	52.00	287.00	0.00	0.00	-1214.35	0.7M	0.38	0.00	80.00	-18.00	0.36	2.80	0.00	0.00
Maximum	250.00	227.00	130.00	457.00	294.00	842.00	0.73	242.00	7215.65	20.2M	1.18	1147.00	401.00	91.00	1.91	12.50	1.00	1.00

Appendix-B2. Detailed model results (M1 – M11).

	M1 (non-sign controls included)				M2 (factory ID control excluded)				M3 (factory ID1 included)				M4 (factory ID2 included)				M5 (factory ID3 included)			
	Path weight	*t*-value	Loading	VIF	Path weight	*t*-value	Loading	VIF	Path weight	*t*-value	Loading	VIF	Path weight	*t*-value	Loading	VIF	Path weight	*t*-value	Loading	VIF
Measurement model																				
Development lead time (*DevLT*)																				
M0toM1	-0.11	0.33	0.11	1.05	0.62 ***	5.27	0.76	1.05	0.62 ***	5.38	0.76	1.05								
M1toM2	1.15 ***	3.27	0.72	1.42	0.75 ***	3.43	0.59	1.42	0.75 ***	3.59	0.59	1.42								
M2toM3	0.81 ***	3.07	0.22	1.37	0.53 ***	2.68	0.16	1.37	0.53 ***	2.79	0.16	1.37								
Hardware complexity (*HWC*)																				
common component count	0.18	0.76	0.50	1.65	0.07	0.58	0.45	1.65	0.07	0.66	0.45	1.65								
product specific component count	0.12	0.70	0.43	1.53	0.28 **	2.20	0.63	1.53	0.28 **	2.25	0.63	1.53								
parts coupling	0.10	0.34	0.49	2.14	0.38 **	2.33	0.68	2.14	0.38 **	2.45	0.68	2.14								
product novelty	0.85 ***	3.33	0.95	1.09	0.71 ***	4.58	0.84	1.09	0.71 ***	4.69	0.84	1.09								
Software complexity (*SWC*)																				
SW novelty	0.76 ***	3.04	0.92	1.16	0.54 ***	3.81	0.77	1.16	0.54 ***	3.76	0.77	1.16								
SW code size	0.12	0.44	0.26	1.02	0.40 ***	3.21	0.52	1.02	0.40 ***	3.41	0.52	1.02								
SW error count	0.40 ***	2.97	0.68	1.15	0.51 ***	5.74	0.74	1.15	0.51 ***	5.61	0.74	1.15								
Ramp-up performance (*RP*)																				
effective utilization	1.00	--	1.00	1.00	1.00	--	1.00	1.00	1.00	--	1.00	1.00								
Structural model (path coefficients)																				
Direct effects																				
SWC --> HWC	0.90 ***	5.07		1.00	0.89 ***	29.20		1.00	0.89 ***	28.20		1.00	0.89 ***	28.20		1.00	0.89 ***	28.20		1.00
HWC --> DevLT	-0.09	0.25		5.17	-0.05	0.36		5.08	-0.05	0.36		5.08	-0.05	0.36		5.08	-0.05	0.36		5.08
SWC --> DevLT	0.70 *	1.74		5.43	0.36 **	1.97		5.91	0.36 *	1.93		5.91	0.36 *	1.93		5.91	0.36 *	1.93		5.91
HWC --> RP	0.03	0.07		6.96	-0.28	1.09		5.10	-0.39	1.52		5.41	-0.30	1.52		5.16	-0.28	1.52		5.10
SWC --> RP	-0.79 **	2.10		7.81	-0.64 **	2.04		6.89	-0.49	1.57		7.44	-0.61	1.57		7.09	-0.65	1.57		6.94
DevLT --> RP	0.55 *	1.79		2.66	0.41 **	2.04		1.95	0.39 **	2.13		1.96	0.40 **	2.13		1.98	0.42 **	2.13		1.96
Control variables																				
linear trend --> DevLT	-0.33 *	1.74		1.12	--	--		--	--	--		--	--	--		--	--	--		--
linear trend --> RP	0.05	0.25		1.71	--	--		--	--	--		--	--	--		--	--	--		--
sales forecast change --> RP	0.12	0.75		1.35	--	--		--	--	--		--	--	--		--	--	--		--
plant age --> RP	0.11	0.74		1.33	--	--		--	--	--		--	--	--		--	--	--		--
production technology novelty --> RP	-0.17	1.26		1.21	--	--		--	--	--		--	--	--		--	--	--		--
planned development lead time --> DevLT	--	--		--	0.74 ***	8.03		1.95	0.74 ***	7.81		1.96	0.74 ***	7.81		1.96	0.74 ***	7.81		1.96
slip --> RP	--	--		--	0.25 **	1.98		1.23	0.29 **	2.32		1.26	0.24 **	2.32		1.28	0.25 **	2.32		1.25
factory ID1...7 --> RP	--	--		--	--	--		--	-0.22 **	2.00		1.15	-0.09 **	2.00		1.07	0.02 **	2.00		1.08
plant location --> RP	--	--		--	--	--		--	--	--		--	--	--		--	--	--		--
Total effects																				
HWC --> RP	-0.02	0.06		--	-0.30	1.13		--	-0.41	1.53		--	-0.32	1.53		--	-0.30	1.53		--
SWC --> DevLT	0.62 ***	3.76		--	0.31 ***	3.04		--	0.31 ***	2.86		--	0.31 ***	2.86		--	0.31 ***	2.86		--
SWC --> RP	-0.43 **	1.98		--	-0.76 ***	5.51		--	-0.72 ***	5.56		--	-0.75 ***	5.56		--	-0.77 ***	5.56		--
Coefficient of determination (R^2)																				
HWC		0.80				0.79				0.79				0.79				0.79		
DevLT		0.62				0.87				0.87				0.87				0.87		
RP		0.37				0.44				0.48				0.44				0.44		
RP (R^2adj)		0.26				0.38				0.41				0.37				0.36		

Notes: N = 46, measurement models for M4 to M9 are left out for clarity as they are in line with M3.

*** p ≤ .01, ** p ≤ .05, * p ≤ .10, two-tailed tests based on 500 bootstrap resamples.

	M6 (factory ID4 included)				M7 (factory ID5 included)				M8 (factory ID6 included)				M9 (factory ID7 included)				M10 (final model)			
	Path weight	*t*-value	Loading	VIF	Path weight	*t*-value	Loading	VIF	Path weight	*t*-value	Loading	VIF	Path weight	*t*-value	Loading	VIF	Path weight	*t*-value	Loading	VIF
Measurement model																				
Development lead time (*DevLT*)																				
M0toM1																	0.62 ***	5.73	0.76	1.05
M1toM2																	0.75 ***	3.60	0.59	1.42
M2toM3																	0.53 ***	2.79	0.16	1.37
Hardware complexity (*HWC*)																				
common component count																	0.07	0.56	0.45	1.65
product specific component count																	0.28 **	2.18	0.63	1.53
parts coupling																	0.38 **	2.29	0.68	2.14
product novelty																	0.71 ***	4.76	0.84	1.09
Software complexity (*SWC*)																				
SW novelty																	0.54 ***	3.85	0.77	1.16
SW code size																	0.40 ***	3.22	0.52	1.02
SW error count																	0.51 ***	5.18	0.74	1.15
Ramp-up performance (*RP*)																				
effective utilization																	1.00	--	1.00	1.00
Structural model (path coefficients)																				
Direct effects																				
SWC --> HWC	0.89 ***	28.20		1.00	0.89 ***	28.20		1.00	0.89 ***	28.20		1.00	0.89 ***	28.20		1.00	0.89 ***	30.11		1.00
HWC --> DevLT	-0.05	0.36		5.08	-0.05	0.36		5.08	-0.05	0.36		5.08	-0.05	0.36		5.08	-0.05	0.36		5.08
SWC --> DevLT	0.36 *	1.93		5.91	0.36 *	1.93		5.91	0.36 *	1.93		5.91	0.36 *	1.93		5.91	0.36 *	1.93		5.91
HWC --> RP	-0.26	1.52		5.93	-0.25	1.52		5.14	-0.23	1.52		5.38	-0.29	1.52		5.16	-0.39 *	1.69		5.40
SWC --> RP	-0.65	1.57		7.15	-0.59	1.57		7.02	-0.63	1.57		6.90	-0.63	1.57		6.94	-0.44	1.47		7.87
DevLT --> RP	0.42 **	2.13		1.97	0.43 **	2.13		1.95	0.36 **	2.13		2.37	0.42 **	2.13		1.97	0.36 *	1.90		2.02
Control variables																				
linear trend --> DevLT	--	--		--	--	--		--	--	--		--	--	--		--	--	--		--
linear trend --> RP	--	--		--	--	--		--	--	--		--	--	--		--	--	--		--
sales forecast change --> RP	--	--		--	--	--		--	--	--		--	--	--		--	--	--		--
plant age --> RP	--	--		--	--	--		--	--	--		--	--	--		--	--	--		--
production technology novelty --> RP	--	--		--	--	--		--	--	--		--	--	--		--	--	--		--
planned development lead time --> DevLT	0.74 ***	7.81		1.96	0.74 ***	7.81		1.96	0.74 ***	7.81		1.96	0.74 ***	7.81		1.96	0.74 ***	7.59		1.40
slip --> RP	0.25 **	2.32		1.25	0.26 **	2.32		1.23	0.24 **	2.32		1.27	0.26 **	2.32		1.23	0.27 **	2.30		1.24
factory ID1...7 --> RP	-0.02 **	2.00		1.30	0.19 **	2.00		1.37	0.10 **	2.00		1.38	0.05 **	2.00		1.04	--	--		--
plant location --> RP	--	--		--	--	--		--	--	--		--	--	--		--	0.22 **	2.53		1.20
Total effects																				
HWC --> RP	-0.28	1.53		--	-0.27	1.53		--	-0.25	1.53		--	-0.31	1.53		--	-0.41 *	1.74		--
SWC --> DevLT	0.31 ***	2.86		--	0.31 ***	2.86		--	0.31 ***	2.86		--	0.31 ***	2.86		--	0.31 ***	2.86		--
SWC --> RP	-0.76 ***	5.56		--	-0.67 ***	5.56		--	-0.73 ***	5.56		--	-0.76 ***	5.56		--	-0.68 ***	5.06		--
Coefficient of determination (R^2)																				
HWC		0.79				0.79				0.79				0.79				0.79		
DevLT		0.87				0.87				0.87				0.87				0.87		
RP		0.44				0.46				0.44				0.44				0.48		
RP (R^2adj)		0.36				0.39				0.37				0.37				0.41		

Notes: N = 46, measurement models for M4 to M9 are left out for clarity as they are in line with M3.

*** p ≤ .01, ** p ≤ .05, * p ≤ .10, two-tailed tests based on 500 bootstrap resamples.

	M10a (TRU_EXE = 4 weeks)				M10b (TRU_EXE = 8 weeks)				M10d (TRU_EXE = 16 weeks)				M10e (TRU_EXE = 20 weeks)				M11 (M10 incl. interaction effect)			
	Path weight	*t*-value	Loading	VIF	Path weight	*t*-value	Loading	VIF	Path weight	*t*-value	Loading	VIF	Path weight	*t*-value	Loading	VIF	Path weight	*t*-value	Loading	VIF
Measurement model																				
Development lead time (*DevLT*)																				
M0toM1	0.58 ***	4.76	0.73	1.05	0.61 ***	4.74	0.76	1.05	0.62 ***	5.47	0.77	1.05	0.58 ***	4.74	0.73	1.05	0.62 ***	5.73	0.76	1.05
M1toM2	0.79 ***	3.75	0.61	1.42	0.76 ***	3.53	0.60	1.42	0.74 ***	3.77	0.58	1.42	0.79 ***	3.53	0.60	1.42	0.75 ***	3.60	0.59	1.42
M2toM3	0.56 ***	2.79	0.17	1.37	0.53 **	2.57	0.16	1.37	0.54 ***	2.63	0.17	1.37	0.58 **	2.57	0.19	1.37	0.53 ***	2.79	0.16	1.37
Hardware complexity (*HWC*)																				
common component count	0.04	0.26	0.39	1.65	0.09	0.58	0.41	1.65	0.10	0.81	0.44	1.65	0.08	0.41	0.41	1.65	0.07	0.56	0.45	1.65
product specific component count	0.21	1.38	0.51	1.53	0.20	1.31	0.55	1.53	0.36 ***	2.84	0.69	1.53	0.32	0.62	0.62	1.53	0.28 **	2.18	0.63	1.53
parts coupling	0.21	1.01	0.52	2.14	0.36 *	1.80	0.62	2.14	0.39 **	2.18	0.70	2.14	0.29 *	1.80	0.62	2.14	0.38 **	2.29	0.68	2.14
product novelty	0.85 ***	7.26	0.94	1.09	0.78 ***	5.21	0.89	1.09	0.66 ***	3.57	0.80	1.09	0.75 ***	5.21	0.87	1.09	0.71 ***	4.76	0.84	1.09
Software complexity (*SWC*)																				
SW novelty	0.69 ***	4.73	0.88	1.16	0.59 ***	3.53	0.82	1.16	0.53 ***	3.18	0.76	1.16	0.62 ***	3.53	0.83	1.16	0.54 ***	3.85	0.77	1.16
SW code size	0.28 **	1.98	0.41	1.02	0.33 **	2.30	0.45	1.02	0.48 ***	3.33	0.59	1.02	0.41 **	2.30	0.53	1.02	0.40 ***	3.22	0.52	1.02
SW error count	0.41 ***	3.39	0.68	1.15	0.50 ***	4.09	0.74	1.15	0.45 ***	4.88	0.68	1.15	0.40 ***	4.09	0.66	1.15	0.51 ***	5.18	0.74	1.15
Ramp-up performance (*RP*)																				
effective utilization	1.00	--	1.00	1.00	1.00	--	1.00	1.00	1.00	--	1.00	1.00	1.00	--	1.00	1.00	1.00	--	1.00	1.00
Structural model (path coefficients)																				
Direct effects																				
SWC --> HWC	0.90 ***	27.34		1.00	0.89 ***	25.83		1.00	0.89 ***	27.78		1.00	0.90 ***	28.21		1.00	0.89 ***	26.96		1.00
HWC --> DevLT	-0.05	0.28		5.41	-0.04	0.27		5.07	-0.09	0.63		5.14	-0.10	0.63		5.41	-0.07	0.54		5.10
SWC --> DevLT	0.37 *	1.81		6.16	0.35 *	1.86		5.84	0.40 **	2.10		5.93	0.43 **	2.05		6.18	0.27 **	1.98		6.38
*SWC*HWC --> DevLT*																	0.17	1,62		1.43
HWC --> RP	-0.57	1.50		6.04	-0.43	1.35		5.53	-0.42 *	1.77		5.49	-0.28	1.60		5.91	-0.39	1.51		5.91
SWC --> RP	0.24	0.49		8.97	-0.19	0.47		8.16	-0.30	1.19		7.84	-0.12	1.15		8.55	-0.44	1.28		8.55
DevLT --> RP	0.12	0.47		2.10	0.17	0.79		2.03	0.43 **	2.00		2.01	0.35 **	2.06		2.09	0.35 *	1.91		2.09
Control variables																				
linear trend --> DevLT	--	--		--	--	--		--	--	--		--	--	--		--	--	--		--
linear trend --> RP	--	--		--	--	--		--	--	--		--	--	--		--	--	--		--
sales forecast change --> RP	--	--		--	--	--		--	--	--		--	--	--		--	--	--		--
plant age --> RP	--	--		--	--	--		--	--	--		--	--	--		--	--	--		--
production technology novelty --> RP	--	--		--	--	--		--	--	--		--	--	--		--	--	--		--
planned development lead time --> DevLT	0.72 ***	7.47		1.37	0.73 ***	7.80		1.39	0.73 ***	7.75		1.38	0.72 ***	7.59		1.37	0.77 ***	9.58		1.37
slip --> RP	0.03	0.21		1.29	0.35 **	2.50		1.26	0.12	1.04		1.23	0.04	1.06		1.26	0.26 **	2.28		1.26
factory ID1...7 --> RP	--	--		--	--	--		--	--	--		--	--	--		--	--	--		--
plant location --> RP	0.08	0.52		1.33	0.16	1.38		1.21	0.22 **	2.28		1.15	0.09 **	2.49		1.20	0.22 **	2.13		1.20
Total effects																				
HWC --> RP	-0.58	1.54		--	-0.44	1.39		--	-0.46 *	1.84		--	-0.32 *	1.69		--	-0.32	1.59		--
SWC --> DevLT	0.33 ***	3.00		--	0.31 ***	2.89		--	0.32 ***	2.96		--	0.34 ***	2.84		--	0.34 ***	2.61		--
SWC --> RP	-0.24	1.09		--	-0.53 ***	2.75		--	-0.54 ***	4.00		--	-0.26 ***	3.95		--	-0.26 ***	4.54		--
Coefficient of determination (R^2)																				
HWC		0.81				0.80				0.80				0.81				0.79		
DevLT		0.87				0.87				0.88				0.88				0.89		
RP		0.12				0.30				0.38				0.12				0.47		
RP (R^2adj)		0.01				0.21				0.30				0.01				0.40		

Notes: N = 46, *** p ≤ .01, ** p ≤ .05, * p ≤ .10, two-tailed tests based on 500 bootstrap resamples.

Appendix-C

Appendix-C1. Descriptive statistics and correlations (Pearson) between variables for chapter 4.

	1	2	3	4	5	6	7	8	9	10	11	12
1. Manufacturing ramp-up performance	1.00											
2. Product complexity	-0.54	1.00										
3. Development lead time	-0.09	0.35	1.00									
4. Ramp-up timing	0.11	0.16	0.19	1.00								
5. Sales forecast change	0.21	-0.11	-0.02	0.04	1.00							
6. Plant ownership	0.11	-0.10	0.17	-0.16	-0.04	1.00						
7. Plant age	0.19	-0.46	-0.06	-0.22	0.09	0.34	1.00					
8. Automation	-0.31	0.08	0.12	0.07	0.16	0.16	0.49	1.00				
9. Plant size	0.05	0.06	0.16	-0.01	-0.05	0.80	0.45	0.33	1.00			
10. Number of key suppliers	0.17	-0.15	0.10	0.11	-0.08	0.12	0.19	-0.02	0.03	1.00		
11. Supplier co-location	0.27	-0.31	0.19	-0.06	0.21	0.30	0.68	0.45	0.43	0.27	1.00	
12. Supplier configuration	0.50	-0.48	-0.07	-0.21	-0.02	0.10	0.49	-0.05	0.15	0.41	0.65	1.00
Mean	0.77	0.00	244.30	0.63	1.07	0.87	6.62	0.15	22746	1.30	1.76	0.63
S.D.	0.20	1.48	85.36	0.49	0.37	0.34	3.08	0.36	9479	0.47	0.77	0.49
Min	0.38	-3.29	82	0.00	0	0.00	3	0.00	2500	1	1	0
Max	1.18	3.04	486	1.00	2	1.00	13	1.00	34468	2	4	1

Appendix-C2. Unstandardized regression results of the findings presented in Table 13.

	R1	R2	R3
Constant	0.606*** (0.085)	0.496*** (0.106)	0.378*** (0.129)
Control variable			
Product complexity	-0.142*** (0.029)	-0.132*** (0.038)	-0.100** (0.038)
Development lead time	0.00066* (0.00034)	0.00055 (0.00035)	0.0004 (0.0004)
Operations characteristics			
Plant age (H1)		0.005 (0.013)	-0.003 (0.013)
Plant size (H2)		0.000005 (0.000005)	0.000003 (0.000005)
Automation (H3)		-0.191** (0.086)	-0.162* (0.094)
Plant ownership (H4)		-0.036 (0.126)	0.033 (0.127)
Ramp-up timing (H5)		0.088 (0.054)	0.109* (0.054)
Supply characteristics			
Number of key suppliers (H6)			-0.023 (0.057)
Supplier co-location (H7)			-0.010 (0.059)
Supplier configuration (H8)			0.158* (0.082)
Sales forecast change (H9)			0.115* (0.065)
Full model (F - and p -statistics)	12.56 [0.000]	5.31 [0.000]	4.62 [0.000]
R^2(adj)	33.90%	40.10%	47.00%

Notes: N = 46, values in parentheses are standard errors, values in brackets are p-values, *** $p \leq .01$, ** $p \leq .05$, * $p \leq .10$, two-tailed tests. All VIF values < 5.1

Appendix-D

Appendix-D1. Data sources in alphabetical order.

	Variable / Indicator	Primary data sources	Secondary data sources (for enhancement)
1	Automation	Plant specific manufacturing configuration documentation	
2	Common component count	Production data management system	
3	Effective utilization	Management information system report	Official milestone review minutes
4	Excess capacity	Management information system report	
5	Final yield	Production data reporting system	Official milestone review minutes
6	Linear trend	Project management reporting database	
7	M0toM1	Project management reporting database	
8	M1toM2	Project management reporting database	
9	M2toM3	Project management reporting database	
10	Number of key suppliers	Sourcing parts list	
11	Parts coupling	Circuit board design tool	
12	Planned development lead time	Project management reporting database	Official milestone review minutes
13	Plant age	Plant specific intranet page	
14	Plant location	Coded by the author	
15	Plant ownership	Coded by the author	
16	Plant size	Plant specific intranet page	
17	Product novelty	Sourcing parts list & product specification	Product fishbone diagrams

18	Product specific component count	Production data management system	
19	Production technology novelty	Manufacturing flow charts (from internal & external operations)	Manufacturing and line configuration files
20	Ramp-up timing	Project management reporting database	
21	Sales forecast change	Management information system report	
22	Slip	Project management reporting database	Official milestone review minutes
23	Supplier co-location	Sourcing parts list (contains supplier IDs and supplier locations)	Official sourcing milestone review minutes
24	Supplier configuration	Sourcing parts list (contains supplier IDs and supplier locations)	Official sourcing milestone review minutes (contains tool shop locations)
25	SW code size	Compiler log files	
26	SW error count	Error management database	
27	SW novelty	Requirements management database	
28	Total product ramp-up performance	Management information system report	Official milestone review minutes

Appendix-D2. Questionnaire template.

Please fill in the green fields

--> try to be as specific as possible!

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Your **Name**:

Your **PCC site**:

Your **Program**:

Was the program an **"engine lead"** program?

- **Yes** - please list the engine name
- **No** - please list from where the engine was copied

Please list all **functional modules** for this program that were new to your PCC site:

Please list all new **technologies** for this program that were new to your PCC site

What was the **pre-production site**?

During which week was the **B3 build** (just state the week and the year e.g. 12-07)

What was the **lead factory**?

Which factories (ENO and SOP) have been ramped-up at a later stage?

Please list all new **manufacturing processes** that had to be implemented in the lead factory

What kind of **product specific production hardware did you reuse** from previous programs (mark with an "x")

- PF adapters
- Flali adapters
- Finui adapters
- Label adapters
- FA1 PSPHW
- FA2 PSPHW
- Others (specify)

Was the product **ATO compatible** and how many **BTR variants** did you have at ramp-up?

How many **variable parts** did the product have?

How many **mechanics suppliers** have been verified and available for the lead factory ramp-up?

Did you have an **E2.5 mass production simulation** BEFORE the official E3/PD3 for all parts?
(if not for all parts then please list the approximate % of parts for which you did an E2.5)

Did you **verify the E2.5 parts** during an NPI build before ramp-up?
(if not please list the approximate % of parts you verified in the E2.5)

Please mark all team members that had prior **program experience** in Nokia programs with an "x"

- PPM
- OLPM
- Materials Project Manager
- Test Manager
- Product Manager
- R&D Manager

In how many programs was the **project team** team involved simultaneously?

Was the **market demand for the product** at the ramp-up as expected, higher or lower?

What were the **biggest obstacles during the ramp-up phase** that affected the **MFR**?

What were the **biggest obstacles during the ramp-up phase** that affected the **volume output**?

Please mark all **development workpackages that have been outsourced** to an JRD company (e.g. FIH, Jabil etc.) with"x"

- Mechanics design
- Electronics design
- Product testing
- Operations work (DFM, test development etc.)
- Sourcing tasks
- Program was done in full JRD mode

End of the questionaire --- thank you very much for your help!