The Impact of Complexity, Rate of Change and Information Availability on the Production Planning and Control Structure: Evidence from Medium-Sized Dutch Discrete Manufacturing Firms

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THE IMPACT OF COMPLEXITY, RATE OF CHANGE AND INFORMATION AVAILABILITY ON THE PRODUCTION PLANNING AND CONTROL STRUCTURE: EVIDENCE FROM MEDIUM-SIZED DUTCH DISCRETE MANUFACTURING FIRMS°

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Abstract

The organizational theory literature argues that the more uncertain the environment, the more likely the firm's operational decision structure is decentralized. However, it remains unclear which uncertainty dimensions (i.e. complexity, rate of change and lack of information) impacts the production planning and control structure the most given today's turbulent manufacturing environments. Based on 206 responses from medium sized Dutch discrete parts manufacturing firms, this study retests the impact of these uncertainty dimensions. This study indicates that each dimension of uncertainty affects the production planning and control structure in a different way. In general, complexity, rate of change and lack of information result in a decentralization of the operational planning and control decision structure, but at the same time a centralization of the customer-order processing decision structure.

Keywords: empirical research method, structural equations model, uncertainty, production planning and control structure.

1 Introduction

In today's hypercompetitive manufacturing environments firms must be flexible and agile. In theory, an effective strategy to gain flexibility and agility is to decentralize by implementing resource groups in a product-oriented manufacturing setting (Stalk and Hout, 1990). This way, problems can immediately be solved locally, within and by the specific resource group, at the time the problem arise (Meal, 1984**;** Koufteros et al., 1998) as it facilitates personal mutual adjustments and face-to-face interactions (i.e. planning and control consultations).

The more uncertain the environment, the more likely the firm's operational decision structure may have a decentralized hierarchy (*e.g.* Burns and Stalker, 1961; Lawrence and Lorsch, 1967; Ford and Slocum, 1977), and the higher the frequency of these planning and control consultations (*e.g.* Galbraith, 1973). However, it remains unclear which uncertainty dimensions (i.e. complexity, rate of change and lack of information) impacts the production planning and control structure the most given today's turbulent manufacturing environments. As a result, we are interested in exploring the extent to which these uncertainty dimensions determine the *Centrality of the production planning and control structure* and the *Frequency of planning and control consultations* in discrete part manufacturing firms. In this paper, we aim to adapt, retest (*e.g.* validating), and extend the theory on these planning and control issues for discrete parts manufacturing environments in general. In addition, we aim to explore *how* the important characteristics of the main Product/Market/Technology (P/M/T) combinations in a specific manufacturing organization relate to the production planning and control structure and consultations. Hence, the *research question* of this exploratory paper is "*how is uncertainty related to the production planning and control structure and the frequency of planning and control consultations given a particular situation specified by its P/M/T combination?* Hence, we aim to extend present theory by exploring internal and external environmental differences, with respect to phenomena like *Complexity* and *Rate of change*, of discrete parts manufacturers with decentralized production planning and control structures versus those who have more central production planning and control structures. Indeed, the objective of this paper is to retest and to detail the impact of various dimensions of uncertainty (i.e. complexity, rate of change and lack of information) on the structure of the planning and control decisions (i.e. locus of control).

The plan of this paper is as follows. In section 2, we discuss the propositions, that is, the relations between the constructs *Complexity* (i.e. variety), *Rate of change*, *Information availability*, and *Centrality of the production planning and control structure* and *Frequency of planning and control consultations* respectively. We distinguish between the complexity and rate of change of the external environmental characteristics that cause uncertainty, i.e. the market perspective of uncertainty, and the complexity and rate of change of the internal environmental characteristics that cause uncertainty, i.e. the product and operations technology perspective of uncertainty. In sections 3, we discuss the research method of this study, including the development of a questionnaire and the statistical procedures to validate the propositions. Subsequently, we discuss the sample, the respondents and the analysis of late/non-response bias. In section 4, we discuss the operational definitions (and corresponding reliability analysis based on Cronbach's alpha) of all constructs. In section 5, we present the results from statistical analysis of the hypothesized relations between the unobserved constructs. In section 5.1, we present a structural model (*e.g.* an extended path analytic model). In section 5.2, we present an alternative structural model with factors obtained from exploratory factor analysis for all indicators. Subsequently, we briefly discuss differences in means (ANOVA) of firms with high a score versus a low score on these factors (*e.g.* complex – non-complex situations, dynamic – stable situations, and information availability). Finally, in section 6, we end this paper with a brief discussion of the results, managerial implications and conclusions.

2 Propositions

2.1 Uncertainty as complexity, rate of change and information availability of the P/M/T characteristics

Hatch (1996) states that organizations traditionally consider *uncertainty* as a property of the environment resulting from two powerful forces: (environmental) complexity and rate of change. *Complexity* refers to the number and variety of the elements in an environment characterized by the major Product/Market/Technology combinations. In other words, if we decompose *Complexity*, we may identify various elements of the Product/Market/Technology combinations that make the situation appear complex. Note that in this paper, we only objectively study uncertainty from a rationalist perspective. Consequently, the complexity of a specific situation is determined by (Flood, 1987):

- The size of the situation as measured by the number of elements that are recognized (*e.g.* the number of products, customers, orders, suppliers, resources, and so on).
- The number of interactions which occur between the elements (*e.g.* the entanglement between departments and cells, or the entanglement between the manufacturer and suppliers).
- The degree in which relationships are linear or nonlinear.

- The degree of symmetry of the situation—asymmetry results in difficulties in analysis and uneven patterns of behavior. Some parts of a situation may have *Rate of change* that function over a different time-period from others, and this causes difficulties in attempts to reconcile models of such situations.
- The degree of autonomy—some parts of situations may have more autonomy than others, and the result is the setting of different goals and objectives.

In this paper, we only explore complexity caused by the number and variety of elements and the number and variety of interactions between these elements within the Product/Market/Technology combinations of a manufacturing organization. As a result, we do not consider complexity caused by time-dependent patterns between and within the Product/Market/Technology combinations as this can be studied only by exhaustive longitudinal research approaches. Furthermore, we do not consider complexity caused by non-linear relations between constructs as well as varying autonomy of the constructs as these type of issues are extremely difficult to model.

In this paper, we let the manufacturing environment consist of the *external* manufacturing environment, i.e. the market, and the *internal* manufacturing environment, i.e. the manufacturing system, which may be characterized by the products that have to be manufactured, and the (operations) technology to manufacture the products. In general, complexity of the operations technology originates mainly from the division of labor. The manufacturing system then becomes a complex mutually dependent network of workers and machines among which various interactions occur. As the complexity of a system increases, the control of the system becomes harder. Each resource has to be aligned to perform the manufacturing tasks. This can be done well only if the resources and the relations between these resources are coordinated in a timely, complete and reliable fashion. In addition, the challenging task of production planning and control to cope with this internal complexity is complicated by external complexity.

However, numerous authors claim that the construct *Rate of change* in an environment determines uncertainty more than the construct *Complexity* (*e.g.* Burns and Stalker, 1961; Katz and Kahn, 1966; and Mintzberg, 1979) and that higher rates of change advocates organic decentralized organization structures and corresponding production planning and control structures. As a result, the rate of change of the environmental elements (*e.g.* how rapidly these elements change) is even more important for controllability issues, as it is an indicator of the validity of the information on the status of the elements. The higher the *Rate of change*, the more momentary available information is. This is acknowledged in the information perspective of uncertainty, where the lack of information of tasks before actually performing these tasks is the key issue (Duncan, 1972; Galbraith, 1973).

In this paper, we also adopt the information perspective of uncertainty, but only consider its rationalist aspects. That is, we do not consider perceived uncertainty due to important cultural, human nature, personality characteristics, individual competences and the incorrectness of the point of reference of the decision making unit. Hence, we operationalize the higher-order construct *Uncertainty* by *Complexity*, *Rate of change* and *Information availability*. In other words, the higher the level of *Complexity* of the P/M/T combination characteristics the higher the level of *Uncertainty*; the higher the *Rate of change of* the P/M/T combination characteristics, the higher the level of *Uncertainty*; and the higher the levels of *Information availability* prior to task execution, the lower the level of uncertainty.

2.2 Uncertainty and Centrality of the production planning and control structure

To analyze the relationship between the *Centrality of the production planning and control structure* and *Uncertainty* as a property of the specific manufacturing environment, we adopt the definition of manufacturing planning and control of Bertrand et al. (1990) as the coordination of supply and production tasks in manufacturing systems to achieve specific delivery flexibility and delivery reliability at minimum costs. This definition provides directions for appropriate operational definitions of the construct *Centrality of the production planning and control structure*, as it is closely related to the locus of decision-making; see for instance Nahm et al. (2003) and Paswan et al. (1998). Nahm et al. (2003) define the locus of decision-making as the degree to which decisions are made higher versus lower in the organizational hierarchy. Note that this perspective concurs with the propositions of Katz and Kahn (1966) and Mintzberg (1979), that the more uncertain the manufacturing situation is, the more decentralized the production planning and control structure (*e.g.* decision hierarchy) will be. Firms operating in an uncertain environment should delegate decisions to the level where workers may quickly adjust to the changing situations (Doll and Vonderembse, 1991). As a result, we claim that *Uncertainty* is positively related to the *Centrality of the production planning and control structure*. That is, the higher the level of *Complexity* is, the more decentralized the *Production planning and control structure*; the higher the level of *Rate of change* is, the more decentralized the *Production planning and control structure*, the more *Information available*, the more centralized the *Production planning and control structure* is. As a result, we have the following propositions.

> **PROPOSITION 1** *Complexity* is negatively related to the *Centrality of the production planning and control structure.*

PROPOSITION 2 *Rate of change* is negatively related to the *Centrality of the production planning and control structure*

PROPOSITION 3 *Information availability* is positively related to the *Centrality of the production planning and control structure*.

2.3 Uncertainty and Frequency of planning and control consultations

A well-known type of lateral adjustment to cope with uncertainty is the organization of prearranged planning consultations (Gailbrath, 1973), where the frequency of these consultations generally depends on the levels of uncertainty. In addition, Nahm et al. (2003) show that organizations that have a high level of time-based manufacturing practices have communication levels that are fast, easy and abundant, where the level of communication is operationally defined with indicators such as 'lots of communications are carried out among managers'. As a result, we propose the following propositions.

PROPOSITION 4 *Complexity* is positively related to the *Frequency of planning and control consultations*.

PROPOSITION 5 *Rate of change* is positively related to the *Frequency of planning and control consultations*.

PROPOSITION 6 *Information availability* is negatively related to the *Frequency of planning and control consultations*.

3 Research method

The propositions of this study are validated with the help of empirical research (i.e. survey research) in the Dutch discrete industry. The analytic procedures in this study include the calculation of descriptive statistics, reliability analysis, factor analysis (exploratory and confirmatory), and multi-indicator path analysis (i.e. structural equations modeling) for which we use the statistical software packages SPSS 11 and AMOS 4.0, respectively.

Although most of the indicators in this study are Likert-type ordinal scaled variables, for which we assume that they fully represent their underlying continuous variables–*e.g.* we treat them as interval variables, we apply parametric univariate and multivariate procedures. This is quite common in the survey literature (see for instance Klem, 1995), provided that the kurtosis and the skewness of each variable is smaller than 7 respectively 2 (West et al., 1995). A classical parametric procedure to study the properties of measurement scales and the indicators that make them up is Cronbach's alpha. Hence, reliability is operationalized as internal consistency, which is the degree of inter-correlation among the indicators that comprise a scale (Nunally, 1978). After this step, three possibilities exist. First, as most of the scales are relatively new—which indicates the exploratory nature of this paper—a scale is accepted straightaway if it has a reasonably strong alpha value (at least .60). Second, scales with alpha values near .60 (*e.g.* .45 − .60) are further analyzed to determine whether alpha can be improved by the removal of one or more indicators. We proceed our analysis with care if alpha values are between .55 and .60, and we investigate the measurement of the scale in a full measurement model of all primary constructs with confirmatory factor analysis as we would like instruments that are both reliable and valid—there is, however, no reason to expect that results from validity and reliability assessments will always coincide. Nevertheless, we claim that validity is more important than reliability, unless the only goal is prediction.

Furthermore, we aim to develop and to validate second-order measurement models (i.e. confirmatory factor analysis) of *Complexity* and *Rate of change*, which is evaluated like any other SEM model, using the goodness of fit measures x^2/d.f. ratio, CFI, NFI, TLI, and RMSEA. By convention, NFI values below .90 indicate a need to respecify the model. Consequently, we require NFI > .90. Furthermore, we require TLI (NNFI) > .95 and indicate models with RMSEA < .065 to have good fit and if .1 > RMSEA > .065 for adequate fit; see for instance Byrne (2001), Hoyle and Panter (1995), Hu and Bentler (1999), and Kline (1998).

There is no point in proceeding to the structural model until *the researcher* is convinced the measurement model is valid. As a result, Kline (1998) urges SEM researchers always to test the pure measurement model underlying a full structural equation model first, and if the fit of the measurement model is found acceptable, then to proceed to the second step of testing the structural model by comparing its fit with that of different structural models (*e.g* with models generated by trimming or building, or with mathematically equivalent models). In this study, we follow Kline's (1998) recommendation.

3.1 Questionnaire development

In this study, we use constructs that cannot be measured directly (*e.g.* latent variables); hence, they have to be operationally defined, by one or more observed indicators. Content validation was assessed through the theoretical basis for the indicators in literature, through the discussion of the preliminary drafts of the questionnaire with academic scholars and through pre-testing of the preliminary draft of the questionnaire in five organizations that have adopted APS systems. Furthermore, we followed the guidelines for writing questions presented by Fink and Kosecoff (1985). For all questions in the questionnaire, we used 5-point scales as much as possible to facilitate the use of statistical analysis without recoding. Since we aim to prevent the situation that a respondent decides to not fill out an answer or guess an answer because he does not know the answer, we decide to thriftily include the option 'Not known'. Note, however, that this option also provides an easy escape for more difficult questions. The same holds for the option 'Not applicable', which we also occasionally use. Furthermore, we occasionally allow the respondents to give multiple answers. Finally, we developed a comprehensive questionnaire of 105 indicators, representing all constructs as well as to check for response bias and authenticity.

3.2 Population and sample selection

As mentioned above, the data for this study were collected through a comprehensive mail survey among Dutch discrete manufacturing firms listed in a commercial database for manufacturing firms with more than 20 employees. The manufacturing firms selected belonged to International Standard Industrial Classification of all Economic Activities (ISIC) codes 20, 27…33, and 36. These categories include firms that manufacture basic metals and fabricated metal products, (electronical) machinery, equipment and apparatus and products of wood; see Table 1. If the ISIC classification for a firm could not be determined, because the respondents failed to identify their firms, or if a respondent filled out another non-process industry ISIC code, the firm was classified as 'other'. Respondents from firms in the process industry were omitted immediately. Hence, these selected firms are from discrete parts manufacturing industries as they involve the manufacture of discrete products, primarily of metal and non-metal fabrication, and exclude all process industries.

There are in total 20,625 Dutch firms listed under the ISIC codes under study. However, according to the research agency EIM BV [1] there are only 5020 firms with more than 20 employees; i.e. 75% of the Dutch firms (with above mentioned ISIC codes) have less than 20 employees. Hence, the population under study is 5020 firms. We phoned 697 of these firms to inquire their willingness to participate in this study, where we primarily asked for a Production and/or Operations Manager. Almost 57% firms agreed to participate, so a package containing a cover letter, a questionnaire and a pre-paid reply envelope, was sent to 394 firms. All respondents were assured of confidentiality. 74 respondents returned the questionnaire within 5 weeks, so there were 320 initial non-respondents. We then decided to phone the firms of which we suspected not to have returned the questionnaire to inquire whether they had sent back the questionnaire yet. If not, we asked again to still fill it out and return it. 51 questionnaires returned without (re)contacting (*e.g.* five weeks after initial sending). 77 non-respondents could not be re-contacted, or were not willing to be contacted by phone again. 48 firms said that, at second thought, they would not fill out the questionnaire, while 37 firms said they already had sent it back (this could be true because respondents were offered the option to fill out the questionnaire anonymously) and 54 firms indicated that they still would send it back. From this group of 202 firms, we had to resend the questionnaire to 23 firms because they had misplaced the questionnaire. In this second round, 83 firms eventually returned the questionnaire.

In all, there were 208 questionnaires returned. However, responses from two firms were excluded from the final sample because these firms did not fulfill the criterion of a discrete manufacturer. Hence, we have 206 useful responses and a final response rate of 29.6% of the 697 phoned firms to gain initial agreement to participate the questionnaire, which is quite acceptable compared to other mail surveys reported in literature; see for instance Malhotra and Grover (1998) and Kotha and Swamidass (2000).

-- Insert Table 1 about here --

-- Insert Figure 1 about here --

3.3 Respondents and response bias

Respondents A comparison of the composition of the 206 responding firms with the composition and characteristics of the entire population (according to EIM BV) gave no reason to expect bias towards any particular branch of discrete parts manufacturing industry. However, comparison of the 206 responding firms with the firm characteristics in terms of number of employees of the entire population indicates that small firms are somewhat underexposed; see Table 1. This is, however, of no burden, as small firms are generally managed centrally by one factory manager, often the founding entrepreneur, independent of the level of uncertainty. Hence, we claim that for small firms the type of decision structure is not an appropriate indicator of the planning and control requirements of that specific situation. As a result, we like medium-sized and larger firms to be overrepresented in our sample compared with small firms. With respect to respondents with more than 50 employees the sample reflects the firms with more than 50 employees in the entire population fairly well; see Figure 1.

Furthermore, with respect to the type of respondent, we conclude that at least 46% were Production- or Operations Managers. As the letter that accompanied the questionnaire primarily asked the survey be completed by a Production- or Operations Managers that was simultaneously responsible for manufacturing management and had knowledge of planning and control issues, some firms decided that this responsibility lied with the general manager, the technical manager, or even the quality manager (*e.g.* the latter types are grouped under others; see Figure 2).

-- Insert Figure 2 about here --

Non-response bias As we actively re-phoned non/late-respondents to fill out and return the questionnaire, we might as well consider the group of late-respondents (81) as equivalent of the group of non-respondents for purpose of non-response bias tests, and compare the late respondents with the 74 early-respondents that returned their questionnaire within 5 weeks with respect to 1) type of industry, 2) number of employees, and 3) turnover. This comparison did not reveal any statistically significant differences.

4 Operational definitions

4.1 Centrality of the production planning and control structure

Numerous researchers have developed measurement items for decentralization (*e.g.* Ford and Slocum, 1977; Miller and Dröge, 1986, Nahm et al., 2003). Vickery et al. (1999) and , Germain et al. (1994) measured decentralization by having the respondents select the level in the organization that had the authority to make certain decisions, as the production planning and control structure within discrete parts manufacturers is generally a hierarchical one, in which the decisions function is delegated to various levels of centrality. This concurs with the planning hierarchy proposed by Anthony (1965) and Thomas and McClain (1993). As a result, we operationally define the *Centrality of the production planning and control structure* with the indicators 1) 'decision level of order acceptance', 2) 'decision level of due date quoting', 3) 'decision level of capacity planning of departments', 4) 'decision level of resource loading', 5) 'decision level of sequencing', 6) 'decision level of dispatching', and 7) 'decision level of material availability check'. The corresponding answering options are {central by management, central by a staff department, decentral by a production leader or teamleader, decentral on the shop floor by an operator} (Q103, i.e. question 103 of the questionnaire). Hence, we recoded these indicators into values of a 5-points scale. Subsequently, from Table 3, we observe that the value of Cronbach's alpha is .7228, which indicates that the measurement of this construct is quite accurate. However, we also note from Table 3 that the correlation coefficient between the indicators 'decision level of order acceptance' and 'decision level of due date quoting' is much higher ($r_{i\,=}$ .4856) than the correlation coefficient between the indicators 'decision level of order acceptance' and any other indicator. As a result, we suspect these two indicators to measure another dimension of the construct *Centrality of the production planning and control structure* then the remaining indicators in the scale.

This is confirmed by a factor analysis (KMO = .683, p_{BTS} = .000), for which we obtain two factors with eigenvalues greater than 1 and small construct correlation coefficients (r_f = .024); see Table 2. In other words, the seven indicators do not measure only one dimension of *centrality of decision making*, but actually measure two separate centrality related constructs, which we indicate as *Planning decisions centrality* and *Customer-order processing (COP) decisions centrality*. Note, that with a Cronbach's alpha of .7302 respectively .6448 these operational definitions are sufficiently reliable.

-- Insert Table 2 about here --

4.2 Frequency of the planning and control consultations

To operationally define *Frequency of the planning and control consultations,* we use the indicators 1) 'frequency of planning consultations between managers on production management level', 2) 'frequency of planning consultations between production management and team leader/sector manager', 3) 'frequency of planning consultations (FPM) between planner(s) and representatives of groups or functional departments', and 4) 'frequency of planning consultations between production manager and planner(s)'. The corresponding answering options are {1 = once a month, 2 = once per two weeks, 3 = once a week, 4 = twice a week, 5 = every day}; question 102 of the questionnaire (Q102). Note, that with a value of Cronbach's alpha of .6391 (and one factor obtained from factor analysis on these indicators), we consider this operational definition as sufficiently reliable; see Table 3.

4.3 Complexity of the P/MT characteristics

In this section, we discuss our operational definitions of the Product/Market/Technology characteristics that affect complexity. According to Mintzberg (1979), an organization's environment can range from *simple* to *complex* (*e.g.* the complexity dimension) and from *integrated* to *diversified* (*e.g.* the diversity dimension). The complexity (*e.g.* number of elements) of the market affects planning and control through the comprehensibility of the work to be done. This external environment of organizations consists of several elements: customers, material-, hardware- and software suppliers, competitors, financiers, the government, and labor markets and unions. In this paper, only the customers and suppliers of the primary products are directly included (competitors are indirectly included) in the set of relevant market elements. At the input side of the manufacturing system, we distinguish *Supplier complexity*; on the output side (*e.g.* demand side), we distinguish *Customer order complexity*. In other words, an external environment (i.e. the market) is complex to the extent that it requires the organization to have a great deal of sophisticated knowledge about customers and suppliers.

Customer order complexity To operationally define *Customer order complexity*, we use the indicators 1) 'average size of customer order (Q14)', 2) 'average number of orders per month (Q15)', 3) 'type of orders (Q16)', and 4) 'predictability of demand with respect to orders (Q23)'. Table 6 shows that the value of Cronbach's alpha is .7105, which indicates that this operational definition is fairly reliable. However, we already like to mention that the indicator 'predictability of demand with respect to orders (Q23)' also correlates with *Information availability*. As the removal of this indicator only results in a slight decrease of the value of Cronbach's alpha, we removed this indicator from the scale.

Supplier complexity Other important aspects of the external environment are the suppliers of materials and resources. Accurate supply in terms of time, volume, place, and specification is essential for a firm to be able to conduct its transformation process and produce output in the same terms. The number of elements and the comprehensibility of these elements on the input side of the system indicate supplier complexity. Hence, we operationally define supplier complexity by the indicators 1) 'number of suppliers (Q50)', 2) 'number of supplied parts and components (Q51)', 3) 'number of production steps contracted out (Q53)', for which we obtain a value of Cronbach's alpha of .5434 (which is rather low).

In addition, we note that the value of Cronbach's alpha can be increased by removing the indicator 'number of production steps contracted out'. However, this leaves us with only two indicators for this construct, which increases the possibility for an empirically underidentified CFA measurement model. Hence, we postpone the decision whether to remove 'indicator 3' from the operational definition until the analysis of the full measurement model of the *Complexity* constructs; see Table 7.

Product-mix related complexity Important internal organizational characteristics that may result in uncertainty are the characteristics of the products that have to be made, the activities needed to transform the input into the required output, and the technology needed for the transformation. In fact, the characteristics of the 'product' are generally boundary-spanning between the external and the internal environment. In other words, the characteristics of the external environment influence the internal environment via the product characteristics.

If the various products designs have many similarities in terms of commonality of production processes required and commonality of parts (both are strongly linked to modular product design), then a firm can offer a high variety, while at the same time, there is similarity in production; see for instance New (1977). Hence, we operationally define *product-mix complexity* by the indicators 1) 'number of product families (Q25)', 2) 'number of variants per product family (Q26)', and 3) 'number of different end-products (Q28)' for which we obtain a value of Cronbach's alpha of .6526, which is sufficiently high; see Table 7.

Operations technology-related complexity The difficulty to coordinate activities depends on the interrelation between these activities. Thompson (1967) distinguishes three ways in which work can be coupled: 1) pooled task interdependence, 2) sequential task interdependence, and 3) reciprocal task interdependence. *Pooled task interdependence* occurs in cases in which little direct contact is needed between groups, where the output of the organization is primarily the sum of efforts of each group. Members share common resources but are otherwise independent. Groups that differ due to day and night shifts on the same assembly line are an example of groups that operate with pooled task interdependence. Thompson (1967) states that groups operating with pooled task interdependence demand very little coordination. The coordination required can generally be accomplished through the use of rules and standard procedures for routine operations. *Sequential task interdependence* occurs in cases in which members work in series, and the work tasks are performed in a fixed sequence. In general, sequential task interdependence requires more planning and scheduling than pooled interdependence. *Reciprocal task interdependence* occurs in cases in which there is need of exchange of information between workers during the performance of their tasks if the scope of the 'task' is too large for one individual to perform the transformation alone. The members feed their work back and forth among themselves; in effect, each receives inputs from and provides outputs to the others. In addition, there are different types of interdependencies among organizational groups.

Reciprocal interdependent activities require mutual adjustment, planning, scheduling, and rules and procedures as coordination mechanisms. In contrast, pooled interdependent activities only require rules and procedures. In other words, the type of interdependency becomes more complex if the entanglement between activities and between resources increases. As a result, we operationally define *Operations technology complexity* by the following indicators: 1) 'entanglement of production steps (Q40)', 2) 'entanglement of departments (Q43)', 3) 'entanglement of machines (Q44)', 4) number of visiting groups or departments in route (inv), 5) 'number of production steps (Q39)', 6) 'average utilization levels (Q41)', 7) 'number of different types of machines in a department (Q38)', and 8) 'number of levels in Bill-of-material (Q) since this indicates the extent of technology complexity in case of a project lay-out; see Table 8. Note, that with a value of Cronbach's alpha of .6410 this scale is sufficiently reliable.

4.4 Confirmatory factor analysis – complexity

In this section, we discuss the first-order and second-order measurement models of *Complexity*. The final first-order measurement model originated after model trimming of the initial first-order measurement model with the complexity related constructs *Customer order complexity*, *Supplier complexity*, *Product-mix complexity* and *Operations technology complexity*. Unfortunately, all factor loadings on the indicators of the construct *Product-mix complexity*, the factor loadings on the indicators 'entanglement of production steps' and 'number of visiting groups or departments' of the construct *Operations technology complexity,* and the covariances between the construct *Product-mix complexity* and the other constructs appeared to be insignificant. After the removal of the construct *Product-mix complexity* as well as the three indicators for *Operations technology complexity*, we obtained the final first-order measurement model with the constructs *Operations technology complexity*, *Product-mix complexity,* and *Supplier complexity*. This final 1st-order measurement model fits the data according to the relative fit indices (*e.g.* d.f.=51, x^2=88.101, and p_{model} =.001, CFI=.993, NFI=.984, TLI=.989, and $\text{RMSEA}_{[.038,.080]}$ = .060). However, support for convergent validity is somewhat problematic, since the error-terms of some indicators are rather high, and the explained variance of some indicators is low, which might make estimates of factor loadings and path coefficients in a path model less reliable. Although, there have not been established cut-off/threshold values for measurement errors, we develop and analyze a second-order measurement model

In Figure 3, we present a CFA model of the 2nd-order construct *Complexity* with unstandardized and standardized estimates. The unstandardized factor loadings are interpreted as regression coefficients that indicate expected change in the indicator given a 1-point increase in the factor. For example, scores on the 'entanglement of machines" are predicted to increase by .59 points for every 1-point increase in the *Operations technology complexity* factor. Standardized loadings are interpreted as correlations and their squared values as proportions of explained variance. The standardized factor loading of the 'entanglement of machines", for instance, is .38, which means that $.38^2$, or 14.5% of its variance is shared with the *Operations technology complexity* factor. Furthermore, note that the factor loading, as well as the level of explained variance of the construct *Operations technology complexity* is fairly low. Nevertheless, all factor loadings are significant; see Table 4, and (off course) the relative fit indices of the overall model are also acceptable (*e.g.* d.f.=51, x^2=88.101, and p_{model}=.001, CFI=.993, NFI=.984, TLI=.989, and $\text{RMSEA}_{[.038, .080]}$ = .060).

However, for the disturbance terms of the 1st-order constructs, Figure 3 also displays the levels of explained variance of these constructs. Note that almost 55% of the variance of *Supplier complexity* is explained by this model. In addition 50% respectively 12% of the variance of *Customer order complexity* and *Operations technology complexity* is explained by this model. In addition, Figure 3 also displays the squared multiple correlations (R^2) for each indicator, indicating the level of explained variance. As mentioned above, most R^2-values are fairly low. For example, only 8% of the variance of the indicator 'average utilization levels' is explained by this model. Nevertheless, as there are no commonly accepted cut-off measures for the measurement errors, we continue this exploratory paper with this second-order measurement model of complexity.

-- Insert Figure 3 about here --

-- Insert Table 4 about here --

Finally, we examine the critical ratios of differences among (residual) variables, which can be considered as a table of the standard normal distribution to test whether two parameters are equal in the population (Byrne, 2001), which would decrease the number of parameters to be estimated. Given that the values of the critical ratios of differences of the disturbance terms for D1, D2, D3 are less than 1.96 (*e.g.* $p < .05$), the hypothesis that these three residual variances are equal in the population could <u>not</u> be rejected; see Table 5. Given these findings, it seems reasonable to constrain variances related to these three residuals to be equal. As such, the 2nd-order measurement model will be further overidentified with two more degrees of freedom. As a result, we maintain this 2nd-order operational definition of *Complexity* in the analysis of causal effects between the constructs in a structural path analytic model.

-- Insert Table 5 about here --

4.5 Rate of change of P/M/T characteristics

An organization's environment can range from *stable* to *dynamic* (Mintzberg, 1979). Real problems are caused by environmental changes that occur unexpectedly, for which no patterns could have been identified in advance. Of course, this is particularly true if the rate of unexpected changes is high and variable. Therefore, the stability dimension affects planning and control through the predictability of the work to be done. In other words, a dynamic environment makes the organization's work more uncertain or unpredictable. There is not only lack of information on the appearances of the specific activities to perform, but also on the timing of execution. In other words, it is unknown what to do when! In this study, we consider the rate of change of the Product/Market/Technology characteristics and initially distinguish between the rate of change of customer demand, suppliers, products, and operations technology.

Rate of change of customer orders Customer order attributes have to be met by a supply vector that specifies the capabilities of the manufacturer. Generally, the supply vector will often not fully meet the actual demand vector. On the one hand, the supplier may be put in default if he delivers the product too late. On the other hand, actual customer orders may be changed. As a result, uncertainty of the customer order (and corresponding aggregated customer demand) is the result of the complexity and the rate of change of demand and order attributes.

Numerous indicators to measure the extent of *Rate of change* can be developed. However, to keep the questionnaire concise, we only asked for a few indicators (which is regrettable a posteriori), as we operationalized *Rate of change of customer orders* by the indicators 1) 'rate of change of size of customer orders (Q64)', 2) 'rate of change of number of orders per month (Q65)', and 3) 'rate of change of number of customer specific parts in end-product (Q61)', for which we obtain a value of Cronbach's alpha of only .5333. From Table 9, we note that the removal of the 3rd indicator would increase the value of Cronbach's alpha, but it also increases the chance of empirically underidentification (*e.g.* Klein, 1998) in the measurement model (which is to be discussed in the next section), given the fairly low correlation coefficients obtained in this study. Hence, we postpone the final judgment on maintaining the scale until after the analysis of the first-order measurement model of *Rate of change*.

Rate of change of suppliers We operationalized *Rate of change of suppliers* by the indicators 1) 'rate of change of number procured and subcontracted parts (Q62)', and 2) 'rate of change of supplied parts on stock (Q63)', for which we obtain a value of Cronbach's alpha of .5259, which is too low to indicate this scale as reliable.

Rate of change of products We operationalized *Rate of change of products* by the indicators 1) 'rate of change of number of end-products (Q56)', 2) 'rate of change of number of variants per product family (Q57)', and 3) 'rate of change of number of different modules (Q58)', for which we obtain a sufficiently large value of Cronbach's alpha of .7164.

Rate of change of operations Technology We operationalized *Rate of change of operations Technology* by the indicators 1) 'rate of change of number of different routes (Q59)', and 2) 'rate of change of number of production steps (Q60)', for which we obtain a value of Cronbach's alpha of .5836, which is also rather low.

As a result, the constructs *Product change* and *Operations technology change* have scales with low values of Cronbach's alpha and both scales have only two indicators, which increases the possibility of empirical underidentification of the first-order measurement model of the *Rate of change*. We therefore applied factor analysis on the indicators of these constructs and obtained a third factor with a value of Cronbach's alpha of .5968. As this value is near .60, we continue our (reliability) analysis with the measurement model of *Rate of change* that comprises the constructs *Product change* and *Customer order change* and *Rate of change rest.*

4.6 Confirmatory factor analysis – Rate of change

In this section, we present the final second-order measurement models of *Rate of change*. As was expected from the fairly low value of Cronbach's alpha, the factor loading on the indicator 'rate of change of number of different routes (Q59)' of *Rate of change rest* appeared to be non-significant. If we omit this indicator, we obtain a first-order measurement model that fits the data according to the relative fit indices except for RMSEA which is large, but still lies within its bounds (*e.g.* d.f.= 24, x^2=87.723, and p_{model} =.000, CFI=.986, NFI=.981, TLI=.974, and $\text{RMSEA}_{[.089,\ .140]}$ =.114).

In Figure 4 , we present a 2nd-order CFA model of *Rate of change*. Note, that, this figure also displays the levels of explained variance of the 1st-order constructs. For example, 97% of the variance of *Customer order change* is explained by this model as well as 45% and 38% of the variance of *Product Rate of change* and *Rate of change rest*, respectively. Furthermore, all factor loadings for the 2nd-order constructs *Rate of change* are all significant and sufficiently large. Furthermore, note that this measurement model explains 67% of the variance of the indicator 'rate of change in the number of variants in a product family (Q57)'. In contrast, it only explains 7% of the variance of the indicator 'rate of change in the number of production steps (Q60)'.

In all, we would accept this 2nd-order measurement model. Nevertheless, as the values of the critical ratios of differences of the disturbance terms for D4, D5, D6 are less than 1.96 the hypothesis that these three residual variances are equal in the population could not be rejected; see Table 5. Given these findings, we constrain the variances related to these three residuals to be equal. As such, the 2nd-order level of the model will be overidentified with two degrees of freedom, and we maintain this 2nd-order measurement model for causal analysis in the structural model.

-- Insert Figure 4 about here --

4.7 Information availability

Several authors claim that the construct *Information availability* is a major determinant of uncertainty (*e.g.* Galbraith 1973; Mintzberg, 1979), where the lack of information of tasks before actually performing these task is the key issue. However, as the main objective of this paper is to explore the relationship between *Uncertainty* and the *Centrality of the production planning and control structure* and *Frequency of planning and control consultations*, we operationally define *Information availability* (Q37) by the indicators 1) 'the extent to which complete product information is available at the time of planning', 2) 'the extent complete processing time information is available at the time of planning', 3) 'the extent material availability information is available at the time of planning', 4) 'the extent to which information is available on the availability of operator capacity at the time of planning', and 5) 'the extent to which information is available on the availability of machines capacity at the time of planning', ranging from full availability until full unavailability of information.

From Table 10, we note that reliability analysis of this scale give a Cronbach's alpha value of .7971, which indicates that it is sufficiently reliable. In addition, factor analysis (KMO = .744) results in only one factor with 'eigenvalue' of 1.

4.8 Confirmatory factor analysis – planning and control requirements

In this section, we discuss part of the measurement models for *Planning and control requirements* plus *Information availability.* Although the fit indices of the initial first-order measurement model of the constructs *Frequency of planning and control consultations*, *COP decisions centrality*, *Planning decisions centrality*, and *Information availability* are d.f.=98, x^2= 212.334, and p_{model}=.000, CFI=.984, TLI=.978, NFI=.971, and $\text{RMSEA}_{[.062,.089]}$=.075, the factor loadings on the indicators 'frequency of planning consultations between managers on production management level', and 'frequency of planning meeting between production manager and planner(s)' of the construct *Frequency of planning and control consultations* appeared to be non-significant; see Figure 5. In addition, covariances between 1) *Frequency of planning and control consultations* and *Planning decisions centrality*, 2) *Information availability* and *Frequency of planning and control consultations*, 3) *Information availability* and *Planning decisions centrality* are also non-significant. In addition, from the analysis of the comprehensive measurement model of all constructs, we note that the covariances between *Frequency of planning and control consultations* and the 2nd-order constructs *Complexity* and *Uncertainty* are also non-significant. This is, however, not the case for *Information availability.* Hence, the construct *Frequency of planning and control consultations* is removed from this measurement model, as well as from the path analytic model to be discussed in section 5.1.

-- Insert Figure 5 about here --

4.9 Secondary constructs and remaining indicators

As we also aim to investigate 1) spurious relationships between possibly causal effects of the 'primary' constructs and *Size*, and 2) the effect of the type of production planning and control structure given a specific degree of environmental uncertainty on *Financial performance*, we briefly discuss our operational definitions of these 'secondary' constructs.

Size We operationally define the construct *Size* by the indicators 'turnover (Q2)', 'number of employees (Q7)', 'number of production related managers (Q10)', and 'number of employees with at least a bachelor degree on logistics (Q11)', for which we have a value of Cronbach's alpha of .7507; see Table 11. Furthermore, factor analysis of these indicators results in only one factor. Hence, we consider this operational definition to be reliable.

Financial performance In concurrence with the operational definitions proposed by Maani et al. (1994) and Fynes and Voss (2001), we operationally define the construct Financial performance by the indicators 'market share (Q3), 'return on investment (Q4)', 'return on sales (Q5)', and 'growth of turnover (Q6)'. However, the value of Cronbach's alpha (.5589) for this operational definition is rather low: see Table 12, hence we omit the indicators 'market share (Q3)', and 'growth of turnover (Q6)' to obtain a value of Cronbach's alpha of .5969.

4.10 Brief discussion of the operational definitions

From the measurement models discussed in previous sections, we know that it is not possible to develop an appropriate 3rd-order construct *Uncertainty*. Furthermore, from the measurement models we concluded that there were no significant associations with the construct *Frequency of planning and control consultations*, hence we only have left the meta-hypothesis displayed in Figure 6 that states that *Complexity* and *Rate of change* are negatively related to the *Centrality of production planning and control structure*. In other words, the more complexity and rate of change in the environment, the more decentralized the production planning and control structure is. Furthermore, *Information availability* is positively related to the *Centrality of production planning and control structure.*

-- Insert Figure 6 about here --

5 Results

In this section, we discuss the results of hypothesis testing with the help of a structural equations model (*e.g.* path analysis). In addition, we use exploratory factor analysis to explore alternative factors to develop an alternative structural model. Furthermore, for each factor, we categorize respondents in a group that have a low score on the factor and a group of respondents that score high on the factor, and use ANOVA analysis to explore differences in means of all other factors.

5.1 A structural model

In this section, we discuss the final structural model (and statistical equivalents) that we aimed to study in the first place; see Figure 7. This model fits the data according to the relative fit indices (*e.g.* d.f.=487, x^2 =830.697, p_{model} =.000, CFI=.978, NFI=.949, TLI=.975, and $\text{RMSEA}_{[.052,.065]}$ =.059). Furthermore, all significant paths are displayed with normal arrows; non-significant paths were removed but are still displayed in Figure 7 with dashed arrows. Hence, there are no significant direct causal relationships between *Information availability* and *Rate of change,* and between *Information availability* and *Planning decision centrality* respectively. There are, however, only significant relationships between *Complexity* and the constructs *COP decision centrality* and *Planning decision centrality.* Note that the direct relationship between *Information availability* and *COP decision centrality* is significant at $p < .1$. Consequently, there are only indirect effects of *Rate of change* and *Information availability* on *Planning decision centrality.* Also displayed in Figure 7 are the disturbances terms and squared multiple correlations (R^2) for each endogenous construct. This indicates the effects of unmeasured variables not included in the model (*e.g.* the unexplained variance in the latent endogenous variables due to all unmeasured causes), and the level of explained variances by the model respectively. Note that this model respectively explains 40% and 29% of the variances of both *COP decisions centrality* and *Planning decisions centrality*, which is fairly reasonable.

The total effects between the constructs in this model is shown in Table 14.

--Insert Table 14 about here --

Complexity The total effect of *Complexity* on *COP decisions centrality* is −.61. The total effect of *Complexity* on *Planning decisions centrality* equals all (standardized) direct effects plus all (standardized) indirect effects, hence .46 + (−.61)(.68) = .05. In other words, there is only a very small impact of *Complexity* on *Planning decisions centrality.*

Rate of change The model indicates only a small indirect effect of *Rate of change* on *COP decisions centrality (*−.17*)* and *Planning decisions centrality* (.03) respectively. We also analyzed statistically equivalent models among which a model that had a significant opposite direction of the relationship between *Complexity* and *Rate of change.* However, based on theoretical considerations, we prefer the model displayed in Figure 7 and conclude that *Rate of change* indirectly affects *COP decisions centrality, Planning decisions centrality* and *Information availability* via *Complexity*.

Information availability The total effect of *Rate of change* on *Information availability* is .07. As the scale of *Information availability* is from full information availability to unavailability, this means that an increase in *Rate of change*, results in a small decrease of the availability of information. In addition, uncertainty because of lack of *Information availability* has only a direct influence on the *COP decisions centrality*, and an indirect influence on *Planning decisions centrality*.

-- Insert Figure 7 about here --

We also examined statistically equivalent models in which the significant causal effects between *Complexity* and *Information availability*, *COP decisions centrality* and *Planning decisions centrality* were assumed to be oppositely directed, but these relations became non-significant. Hence, we state our findings from the final structural model as:

- The higher the complexity, the more centralized the customer-order processing structure (i.e. order entry structure) is;
- The higher the complexity, the more decentralized the detailed operational planning structure is;
- The higher the complexity, the less information is available;
- The less information available, the more decentralized the order entry (COP) structure is;
- The more (de)centralized the order entry structure is, the more (de)centralized the detailed operational planning structure is.

The results from this structural model indicate that uncertainty due to *Rate of change* has almost no impact on the organization of the production planning and control structure (except for order entry decisions) which may be explained by the inertia of discrete parts manufacturers (*e.g.* any short-term disturbance within the internal manufacturing system on the present way of doing things are adapted as business-as-usual). Furthermore, the uncertainty lies in the variance of the number of customer orders per month and the order size; not in the type of products or the production related variables such as rate of change of production routings, the rate of change of the number of production steps and the rate of change of the number purchased or outsource parts. Hence, we postulate that discrete parts manufacturers ‘stick’ with their product-portfolio, which is in concurrence with the findings of the study of Deloitte and Touche (2003) that states that the innovativeness of small and medium-sized Dutch discrete parts manufacturers is too low. Simply stated, discrete parts manufacturing do not make tractors today and motorcycles tomorrow.

Furthermore, based on these results, we postulate that any decision to decentralize (the production planning and control structure) is not based on logistical considerations (*e.g.* from a logistical perspective), but primarily on other considerations, for example social issues. Furthermore, the results indicate that there is no direct relationship between the *Rate of change of* a manufacturing environment and the *Planning decisions centrality* and the *COP decisions centrality* respectively. By the same token, there is no relationship between *Information availability* and the *Planning decisions centrality*. We also did not find relationships between uncertainty in the P/M/T characteristics and the *Frequency of planning and control consultations*. Finally, we did not find any relationships between the 1st-order constructs of *Complexity* (or *Rate of change*) and *Frequency of planning and control consultations*. From an analysis of a structural model with only 1st-order constructs, we note that the construct *Customer order complexity* particularly determines the structure of the decision hierarchy; see Figure 8.

-- Insert Figure 8 about here --

5.2 An alternative model

Convergent validity of the second-order measurement models underlying the structural model displayed in Figure 7 is somewhat problematic. To further investigate the differences between respondents on several types of complexity and rate of change variables and the impact on the production planning and control structure, we therefore also conducted an orthogonal exploratory factor analysis on all indicators from which we obtained 16 independent factors (for the underlying indicators of each factor and scale reliability based on Cronbach's alpha, we refer to the Appendix A). The factors are: *Order complexity* (F1), *Information availability* (F2), *Firm size* (F3), *Planning decision centrality (F4)*, *End-product change* (F5), *Financial performance* (F6), *COP decisions centrality* (F8)*, End-product complexity* (F9), *Supplier complexity* (F10), *Component and part change* (F11), *Delivery time complexity* (F12), *Order change* (F13), *Route change* (F14), *Route complexity* (F15). Note that most of these factors are quite similar to our initial theory-based constructs for which we also found low inter-factor correlation.

The extraction of these factors gives us the opportunity to explore an alternative SEM model, namely one with causal effects between all 1st-order PMT uncertainty related factors and the planning and control related factors. For sake of brevity, we do not display the full measurement model of these 'orthogonal' factors, but refer to the final hybrid model displayed in Figure 9, that fits the data according to the relative fit indices (*e.g.* d.f.=204, x^2=451.591, p_{model} =.000, CFI=.975, NFI=.955, TLI=.969, and RMSEA$_{[.067,.087]}$ =.077), which was obtained after the removal of non-significant relations (*e.g.* $p > .1$) and non-significant factor loadings.

In concurrence with the model displayed in, Figure 8, we note from this alternative model that *Order complexity* influences the *COP decisions centrality* most: the higher the *Order complexity*, the more centralized the *COP decisions* structure. However, *Product complexity* and *Information availability* tend towards a decentralized *COP decisions* structure. In addition, the more centralized the *COP decisions* structure, the more centralized the *Planning decision* structure. However, *Supplier complexity* positively influences the *Planning decisions centrality* ($p<.1$).

-- Insert Figure 9 about here –

5.3 ANOVA analysis

Subsequently, we categorize respondents into a low scoring and a high scoring group for each factor (displayed in the columns in Table 13), and we explore difference in means on all other factors displayed in the rows of Table 13. Note that the diagonal of this table displays the means of the low and high scoring categories for each factor, which is of course significant at $p < .01$.

Column 3): *Order complexity (F1)*—From Table 13, we note that firms that face high order complexity, also have less information available as the scale of *Information availability* is decreasing (from complete availability to unavailable). In addition, these firms have a more central *COP decisions* structure and less *Frequency of planning and control consultations* than firms that face low *Order complexity.* The latter may be the result of the lower scores on *End-product complexity* and *Delivery time complexity.* Furthermore, firms that have high levels of *Order complexity* also have high levels of *Components and parts change.* Finally, we note that the absence of significant differences in means in the other *Rate of change* related factors justifies our choice for the direction of the path between *Rate of change* and *Complexity* of the initial structural model displayed in Figure 7. *Rate of change* is related to *COP decision centrality* and *Planning decisions centrality* via *Complexity.*

Column 4): *Information availability (F2)*—Firms that have less information available (higher scores) also have higher *Order complexity*, higher R*oute complexity*, but lower level of *Delivery time complexity.* Finally, from this analysis we also conclude that *Information availability* is not significantly related to the *Rate of change* related factors, except for *Components and parts change.*

Column 5): *Firm size (F3)*—Firms that are smaller, have higher order complexity but less *Supplier complexity* and less *Route complexity* ($p < .05$). Furthermore, note that there is neither a significant difference in means for *Rate of change* related factors, nor a significant difference in means for *Information availability*.

Column 6): *Planning decision centrality (F4)*—Firms that have more decentralized *Planning decisions* structure have also a higher level of *Order change*, and a more decentralized the *COP decisions* structure. Note, however, that they do not significant differ in *Supplier complexity*, compared to firms that have more centralized *Planning decisions* structure. Hence, the impact of *Supplier complexity* on the *Planning decisions centrality* is only modest. Based on this finding, we should remove the construct *Supplier complexity* from the alternative structural model displayed in Figure 9, or search for spurious relationships.

Column 7): *End-product change (F5)*—Firms that have more *End-product change* also have more *End-product complexity* (F9), *Components and parts change* (F11), and *Order change* (for all: $p < .05$). However, they do not significantly differ on *Frequency of planning and control consultations* or *COP decisions* structure and *Planning decisions* structure.

Column 8): *Financial performance (F6)*—Firms with higher *Financial performance* have significant lower *Order complexity* ($p < .01$) and a more decentralized *COP decisions* structure ($p < .1$).

Column 9): *Frequency of planning and control consultations (F7)*—Firms with higher than average *Frequency of planning and control consultations* have more centralized *Planning decision* structure, higher than average *End-product complexity.* Furthermore, note that firms that have a high *Frequency of planning and control consultations* cannot be discriminated from firms that have a low *Frequency of planning and control consultations* on *Rate of change* related factors.

Column 10): *COP decisions centrality (F8)*—Firms with more decentralized *COP decisions* structure have lower than average *Order complexity*, more decentralized *Planning decisions* structure, higher than average *End-product complexity*, *Financial performance* and *Delivery complexity*, but a lower than average *Components and parts change.*

Column 11): *End-product complexity (F9)*—Firms with higher *End-product complexity* have lower *Order complexity*, which indicates a more project-oriented production of one or more highly composed end-products. Note that these firms have a more decentralized *COP decisions* structure, probably because they also have a higher level of *Route change*, *Order change* and of *End-product change*. These findings strengthen our proposition that *Rate of change* impacts the *Production planning and control structure* only if there simultaneously is *Complexity* and justifies the direction between *Rate of change* and *Complexity* in the structural model displayed in Figure 7.

Column 12): *Supplier complexity (F10)*—Firms that have higher *Supplier complexity* are larger, have more *Order complexity*, but have less *Delivery time complexity*. Note, however, that they do not significantly differ in the *Planning decisions* structure. This might be explained by the fact that the influence of *Supplier complexity* is relatively small or there are other spurious relationships.

Column 13): *Component and part change (F11)*—Firms that have higher levels of *Component and part change* have also higher *Order complexity*, and higher level *Order change*, *End-product change* and *Route change*. In addition, they have less *Information available*. Furthermore, they have more centralized *COP decision* structures which negates the theory that a higher *Rate of change* leads towards more decentralized organic structures. However, from the results of the structural models, we now know that *Order complexity* more strongly determines the centrality of the *COP decision* structure than *Component and part change*.

Column 14): *Delivery time complexity (F12)*—Firms that face higher *Delivery time complexity* have a more decentralized *COP decisions* structure. This was not expected from results of the alternative structural model displayed in Figure 9. Note, however, that firms that face higher *Delivery time complexity* have a lower *Order complexity*, which might explain the more decentralized *COP decision* structure. In addition, they have higher *Frequency of planning and control consultations*, but lower level of *Information availability* (i.e. more information available) as the levels of *Route change* and *Route complexity* are lower.

Column 15): *Order change (F13)*—Firms that have a higher level of *Order change* also have higher levels of *End-product change* and *Components and parts change*. Furthermore, they have higher *End-product complexity*. Nevertheless, they do not significantly differ on *Frequency of planning and control consultations* or *COP decisions* structure and *Planning decisions* structure.

Column 16): *Route change (F14)*—Firms that have higher levels of *Route change* have also higher levels of *End-product change* and *Components and parts change*. Furthermore, note that they have more centralized *COP decisions* structures, which also negates commonly accepted theory.

Column 17): *Route complexity (F15)*—Firms that have higher *Route complexity* are generally larger and have a higher level of *Route change*, but not a higher level of *Order change*. In addition, note that *Route complexity* does not significantly discriminate on *Frequency of planning and control consultations* or *COP decisions* structure and *Planning decisions* structure.

6 Discussion

6.1 Insights and implications

This study indicates that each dimension of uncertainty affects the production planning and control structure in a different way. When organizational uncertainty is high, strategic decision-making authority may be centralized, but operational decision-making authority should be decentralized (Vickery et al., 1999; Nahm et al., 2003). The findings of this study support this insight but also detail the impact of the uncertainty dimensions complexity, rate of change and lack of information on the level of centrality of decision-making. These dimensions result in a decentralization of the operational planning and control decision structure, but at the same time a centralization of the customer-order processing decision structure.

Order complexity influences the *COP decisions centrality* most: the higher the *Order complexity*, the more centralized the *COP decisions* structure. However, *Product complexity* and *Information availability* tend towards a decentralized *COP decisions* structure. In addition, the more centralized the *COP decisions* structure, the more centralized the *Planning decision* structure. However, *Supplier complexity* positively influences the *Planning decisions centrality* ($p<.1$). This seems to indicate that the higher the *Supplier complexity*, the more decentralized the *Planning decisions* structure. However, this relationship requires closer examination. That is, we explore the relationships in the structural model on spurious relationships due to possible 'lurking' variables. From this analysis it appeared that the usage of an ERP system is an important determinant for a more centralized operational planning decision hierarchy; this concurs with the finding of Davenport (1998). From the extended structural model displayed in Figure 10, that fits the data according the relative fit indices d.f.= 345, x^2= 539.895, and p_{model} =.000, CFI=.976, TLI=.971, NFI=.953, and RMSEA$_{[.061,.079]}$ =.070), we note that *Supplier complexity* pleads for the adoption of an ERP system, that, indirectly, leads to a more centralized *Planning* *decision* structure. Furthermore, note that the level of explained variance of the construct *Planning decision* structure is increased to 26%. Note that the constructs *End-product complexity* and *Supplier complexity* have only a small impact (at the significance level of $p<.05$) on the *Planning decision centrality:* see Table 15.

-- Insert Figure 10 about here --

-- Insert Table 15 about here --

In particular the constructs *Order complexity* and *End-product complexity* determine the level of centralization of the decision structure. Note from Figure 10, that the beta coefficient between *End-product complexity* and *COP decisions centrality* is .22; the beta coefficient between *Order complexity* and *COP decisions centrality* is –.57 indicating a stronger effect, which is, of course confirmed by the ANOVA analysis as discussed in the previous section.

In all, we conclude that firms with high *End-product complexity* have higher than average *Frequency of planning and control consultations* and have more decentralized *COP decisions* structures. In contrast, firms with a high *Order complexity* have lower than average *Frequency of planning and control consultations* and have more centralized *COP decisions* structures. In addition, firms with a higher than average *Frequency of planning and control consultations* have a higher than average End-product complexity, but do not differ on *Order complexity*. Finally, firms with more decentralized COP decision structure have a higher than average *End-product complexity* and a lower than average *Order complexity*.

Another interesting finding with managerial implication is that firms with a high score on *Financial performance* have on average a lower level of *Order complexity* and decentralized *COP decision* structures. As a result, organizations that decentralize the structure to cope uncertainty would be well-advised to reduce order complexity first.

6.2 Direction for further research

Another strategy to cope with uncertainty is to enlarge communication channels (e.g. Galbraith, 1973), and to use intelligent manufacturing planning and control systems that simultaneously supports material coordination and planning & scheduling of scarce resource capacity (Stadler and Kilger, 2000). However, ERP systems are centralized systems, often based on the rigid hierarchical MRP paradigm, in which information is stored centrally (*e.g.* Davenport, 1998; Langenwalter, 2000). The structural model in Figure 10 shows that end-product complexity and supplier complexity have a positive effect on the adoption and usage of ERP systems; and that the usage of ERP inclines towards a centralized production planning and control structure.

Advanced Planning and Scheduling (APS) systems can also be characterized as centralized control systems (Stadler and Kilger, 2000; Zijm, 2000). In contrast, kanban control systems are generally decentralized systems. The question remains what the impact of various uncertainty related Product/Market/Technology factors (i.e. complexity, rate of change and information availability) on the adoption and usage of various planning and control methods and systems is. In addition, various planning software systems and methods may have reinforcing or moderating influence on the centrality of the production planning and control structure. Future research could examine these aspects.

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8 Appendix

8.1 Appendix A: Factors from EFA

Construct	**Indicators**
F1: Order complexity	Number of orders per month (INV)
α = .7105 (.7187)	Type of orders
	Order size
F2: Information availability	Information about the products
α = .7917 (.7905)	Information about the processing times
	Information about material availability
	Information about available operator capacity
	Information about available machine capacity
F3: Firm size	Turnover
α = .7507 (.7516)	Number of employees
	Number of production related managers
	Number of employees with at least a bachelor degree on logistics
F5: End-product change	Rate of change in number of end products
α = .7164 (.7124)	Rate of change in number of different modules
	Rate of change in number of products in family
F9: End-product complexity	Number of product families
α = .6003 (.5938)	Number of variants per product family
	Number of modules to build end products with
	Number of different end-products
F10: Supplier complexity	Number of suppliers
α = .5434 (.5435)	Number of supplied parts and components
	Number of production steps contracted out
F11: Component and part change	Rate of change in number of items on stock
α = .5256 (.5310)	Rate of change in number of procured and subcontracted parts
	Rate of change in customer-specific parts in end-products
F12: Delivery time complexity	Frequency of rush orders
α = .6187 (.6287)	Delivery time (INV)
F13: Order change	Rate of change in number of orders per month
α = .5866 (.5933)	Rate of change in order size
F14: Route complexity	Entanglement of departments
α = .5684 (.5705)	Number of different types of machines in a department
	Number of production steps
	Utilization of resources
	Entanglement of machines

8.2 Appendix B: Tables

-- Insert Table 7 about here --

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--Insert Table 9 about here –

-- Insert Table 10 about here --

-- Insert Table 11 about here --

-- Insert Table 12 about here --

	Sample		**Population**	
# Employees	Frequency	%	Frequency	%
< 20	0	0.0%	0	0.0%
20 - 49	39	19.0%	2805	55.9%
50 - 99	73	35.6%	1115	22.2%
> 99	93	45.4%	1100	21.9%
Total valid	205	100.0%	5020	100.0%

Table 1: Comparison of sample and population with respect to number of employees (>20 employees).

Variables (indicators)	***Planning decisions centrality***	***COP decisions centrality***
decision level of order acceptance		.463
decision level of due date quoting		.989
decision level of capacity planning of departments	.511	.352
decision level of sequencing	.663	
decision level of resource loading	.881	
decision level of dispatching	.409	
decision level of material availability check	.368	
Cronbach's alpha	.7302	.6448
Planning decisions centrality	.831	
COP decisions centrality	.024	.995

Table 2: Rotated factor matrix (*Centrality of decision making*) and factor score covariance matrix.

Construct	**Cronbach's alpha**	**Variables (indicators)**	**Pearson correlation**							**Mean**	**SD**	**Alpha if indicator deleted**
Frequency of planning and control consultations	.6391	on production management level	1.0000							3.1946	1.2225	.6155
(*N*=185)		between management and team leader/sector manager	.4323	1.0000						3.7514	1.0998	.4633
		between planner and repr. of group / funct. dpt.	.1599	.4459	1.0000					4.0432	1.2633	.5902
		between production manager and planner	.2301	.3175	.2858	1.0000				3.6757	1.1528	.6036
Centrality of the planning structure	.7228	decision level of order acceptance	1.0000							1.6721	.7151	.7162
(*N*=183)		decision level of due date quoting	.4856	1.0000						1.9235	.6482	.6952
		decision level of capacity planning of departments	.1444	.3815	1.0000					2.1858	.7324	.6687
		decision level of sequencing	.1219	.1678	.3423	1.0000				2.5191	.6564	.6898
		decision level of resource loading	.1422	.1255	.4396	.5779	1.0000			2.5683	.6910	.6649
		decision level of dispatching	.2625	.1929	.2908	.2074	.3290	1.0000		2.2568	.6650	.6930
		decision level of material availability check	.1060	.2326	.2938	.1962	.3111	.3070	1.0000	2.4098	.6941	.7029
COP decisions centrality	.6448	decision level of order acceptance	1.0000							1.6751	.5768	-
(*N*=197)		decision level of due date quoting	.4758	1.0000						1.9289	.5847	-
Planning decision centrality	.7302	decision level of capacity planning of departments	1.0000							2.1979	.7394	.6736
(*N*=187)		decision level of sequencing	.3722	1.0000						2.5294	.6333	.6835
		decision level of resource loading	.4693	.5920	1.0000					2.5722	.6791	.6271
		decision level of dispatching	.3276	.2406	.3644	1.0000				2.2620	.6727	.7064
		decision level of material availability check	.3017	.2060	.3187	.3204	1.0000			2.4118	.6692	.7212

Table 3: Operational definition of planning and control requirements.

			Estimate	C.R	P
Supplier complexity	↔	*Complexity*	.88	2.023	.043
Customer order complexity	↔	*Complexity*	1		
Operations technology complexity	↔	*Complexity*	.33	2.004	.045
Number of Suppliers	↔	*Supplier complexity*	.67	4.908	0
# of supplied parts and components	↔	*Supplier complexity*	1		
Number of steps contracted out	↔	*Supplier complexity*	.46	3.541	0

Order size	↔	*Customer order complexity*	1		
Number of order per month	↔	*Customer order complexity*	.67	6.091	0
Type of orders	↔	*Customer order complexity*	.60	6.583	0
Entanglement of departments	↔	*Operations technology complexity*	.54	3.325	.001
# of different types of machines	↔	*Operations technology complexity*	.65	4.441	0
# of production steps	↔	*Operations technology complexity*	1		
Entanglement of machines	↔	*Operations technology complexity*	.59	3.459	.001
Average utilization levels	↔	*Operations technology complexity*	.38	2.931	.003
# of levels in BOM	↔	*Operations technology complexity*	.51	3.671	0

Table 4: Factor loadings of the 2^{nd}-order measurement model of complexity.

Complexity	D1	D2	D3	Rate of change	D4	D5	D6
D1	0.0			D4	0.0		
D2	0.2	0.0		D5	− 1.6	0.0	
D4	0.3	0.0	0.0	D6	0.1	1.8	0.0

Table 5: Critical ratios of differences among disturbance terms of Complexity and Rate of change.

Construct	**Cronbach's alpha**	**Variables (indicators)**	**Pearson correlation**				**Mean**	**SD**	**Alpha if indicator deleted**
Customer order complexity	.7105	order size	1.0000				3.2113	1.3852	.5895
(*N*=194)		type of orders	.5391	1.0000			3.1701	.9854	.6205
		predictability of order	*.3176*	*.3457*	*1.0000*		*3.5258*	*.8768*	*.7051*
		number of order per month (inv)	.4561	.3810	.2992	1.0000	2.8557	1.3770	.6556

Table 6: Operational definition of Customer order complexity.

Construct	**Cronbach's alpha α**	**Variables (indicators)**	**Pearson correlation**			**Mean**	**SD**	**Alpha if indicator deleted**
Product mix complexity	.6526	number of product families	1.0000			2.8294	1.1411	.7273
(*N*=170)		number of variants per product family	.1736	1.0000		3.1059	1.6749	.5457
		number of different end-products	.3908	.5742	1.0000	3.6059	1.5203	.2782
Supplier complexity	.5434	number of suppliers	1.0000			2.9700	1.0700	.3692
(*N*=200)		number of supplied parts and components	.4307	1.0000		3.0450	1.4641	.3088
		number of production steps contracted out	.1826	.2389	1.0000	2.9800	1.0512	.5819

Table 7: Operational definition of product mix complexity and supplier complexity.

Construct	**Cronbach's alpha**	**Variables (indicators)**	**Pearson correlation**								**Mean**	**SD**	**Alpha if indicator deleted**
Operations technology complexity	.6410	entanglement of production steps	1.0000								4.2258	.6848	.6262
		entanglement of departments	.1614	1.0000							4.5645	1.1910	.5882
		entanglement of machines	.3352	.3142	1.0000						3.9516	1.1815	.5562
(*N*=124)		number of visiting groups or departments in route (inv)	.0224	.3947	.0808	1.0000					3.5081	.9413	.6493
		number of production steps	.1084	.2421	.3448	.0923	1.0000				1.9274	.9892	.5747
		average utilization levels	.0615	.1468	.2511	−.0635	.2664	1.0000			3.2339	1.0524	.6361
		number of different types of machines in a department	.2477	.1616	.4211	−.0129	.3876	.1166	1.0000		3.0726	1.0529	.5906
		levels of BOM	.0761	.0988	.0989	.1000	.2283	.1030	.1852	1.0000	2.3145	.9658	.6364

Table 8: Operational definition of technology complexity.

Construct	Cronbach's alpha	Variables (indicators)	Pearson correlation			Mean	SD	Alpha if indicator deleted
Product Rate of change	.7164	rate of change of number of end-products	1.0000			3.3988	1.0390	.5830
(N=168)		rate of change of number of variants per product family	.1736	1.0000		3.3869	1.0994	.4961
.7413, *N*=193		rate of change of number of different modules	.3908	.5742	1.0000	2.6429	.8977	.7518
Technology Rate of change	.5836	rate of change of number of different routes	1.0000			2.3743	.8289	-
(*N*=187)		rate of change of number of production steps	.4120	1.0000		2.4332	.8293	-
Supplier Rate of change	.5259	rate of change of number procured and subcontracted parts	1.0000			2.9529	.9475	-
(*N*=191)		rate of change of supplied parts on stock	.3592	1.0000		2.7173	.8421	-
Customer Rate of change	.5333	rate of change of size of customer orders	1.0000			3.8095	1.0446	.2069
(*N*=189)		rate of change of number of orders per month	.4088	1.0000		3.7090	.8660	.4794
		rate of change of number of customer specific parts in end-product	.3162	.1195	1.0000	3.2540	1.1294	.5732

* Significant at $p < .01$; ** Significant at $p < .05$

Table 9: Operational definition of rate of change (Rate of change) of products, technology, suppliers and customers.

Construct	Cronbach's alpha	Variables (indicators)	Pearson correlation					Mean	SD	Alpha if indicator deleted
Information availability	.7971	information about the products	1.0000					1.5792	.7236	.7896
(*N*=202)		information about the processing times	.4591	1.0000				1.8713	.9219	.7739
		information about material availability	.2298	.4147	1.0000			2.2021	.8245	.7544
		information about available operator capacity	.3048	.4619	.4636	1.0000		2.0297	.8691	.7116
		information about available machine capacity	.2820	.4184	.4543	.7630	1.0000	1.9158	.8741	.7229

Table 10: Operational definition of Information availability.

Construct	Cronbach's alpha	Variables (indicators)	Pearson correlation				Mean	SD	Alpha if indicator deleted
Size	.7507	turnover	1.0000				3.1150	1.0134	.6699
(*N*=200)		number of employees	.7330	1.0000			3.3800	.9219	.6139
		number of production related managers	.3149	.4384	1.0000		1.6200	.9434	.7305
		number of employees with at least Bachelor degree on logistics	.3253	.3680	.4049	1.0000	2.0600	.9544	.7453

Table 11: Operational definition of Size.

Construct	Cronbach's alpha	Variables (indicators)	Pearson correlation				Mean	SD	Alpha if indicator deleted
Financial Performance	.5589	market share	1.0000				2.3497	1.0088	.5505
(*N*=143)		return on investment	.2287	1.0000			2.356	1.134	.4196

							6	6	
		return on sales	.2314	.4784	1.0000		2.4895	.7399	.4197
		growth of turnover	.1360	.2205	.2756	1.0000	2.9371	1.1881	.5544

Table 12: Operational definition of Financial performance.

Constructs		F1	F2	F3	F4	F5	F6	F7	F8	F9	F10	F11	F12	F13	F14	F15
Order Complexity (F1)	L	2.45***	2.93***	3.31**			3.41***		3.66***	3.25**	3.00***	3.06***	3.56***			
	H	3.90***	3.46***	3.04**			3.02***		2.89***	2.97**	3.42***	3.44***	2.81***			
	T	3.19***	3.18***	3.18**			3.20***		3.18***	3.10**	3.19***	3.23***	3.17***			
Information availability (F2)	L	1.69***	1.41***									1.82**	1.99**			
	H	2.11***	2.42***									2.01**	1.79**			
	T	1.90***	1.90***									1.91**	1.88**			
Firm Size (F3)	L		3.39*	2.55***							3.15**					3.07***
	H		3.15*	4.05***							3.40**					3.44***
	T		3.27*	3.26***							3.26**					3.27***
Planning decisions (F4)	L				2.31***			2.98**	2.71**							
	H				3.33***			2.76**	2.93**							
	T				2.86***			2.86**	2.85**							
End-Product Change (F5)	L					2.57***				2.97*		2.87***		2.93***	3.04*	
	H					3.94***				3.22*		3.50***		3.32***	3.26*	
	T					3.14***				3.10*		3.15***		3.15***	3.15*	
Financial Performance (F6)	L						1.69***		2.26*							
	H						3.03***		2.51*							
	T						2.42***		2.42*							
Frequency of planning and control consultations (F7)	L	3.78**						2.93***		3.48**			3.56*			
	H	3.54**						4.32***		3.76**			3.77*			
	T	3.66**						3.67***		3.63**			3.66*			
COP Decisions Centrality (F8)	L	2.29***			1.89***		1.94*		1.31***	1.92***		2.18***	1.79***		2.17*	
	H	1.79***			2.21***		2.15*		2.49***	2.25***		1.89***	2.14***		2.01*	
	T	2.04***			2.06***		2.05*		2.07***	2.08***		2.05***	2.01***		2.09*	
End-Product Complexity (F9)	L	3.34**				2.97**		2.99**	2.78***	2.16***			2.83***	2.88***		
	H	2.95**				3.43**		3.36**	3.35***	4.11***			3.56***	3.40***		
	T	3.16**				3.16**		3.18**	3.16***	3.18***			3.22***	3.17***		
Supplier Complexity (F10)	L	2.76***		2.86**				3.23*			2.19***					
	H	3.22***		3.17**				2.94*			4.02***					
	T	2.99***		3.01**				3.01*			3.01***					
Component & Part Change (F11)	L	2.99**	3.02*			2.85***			3.36***		3.01**	2.47***		2.87***	2.95**	
	H	3.28**	3.24*			3.55***			2.99***		3.28**	3.95***		3.30***	3.29**	
	T	3.14**	3.13*			3.14***			3.13***		3.13**	3.13***		3.10***	3.13**	
Delivery Time Complexity (F12)	L	3.64***	3.29**					2.95*	2.69***	2.88***	3.25*		2.23***			
	H	2.62***	2.97**					3.22*	3.35***	3.42***	2.98*		3.96***			
	T	3.13***	3.14**					3.09*	3.13***	3.17***	3.13*		3.13***			
Order Change (F13)	L				3.60**	3.59***				3.58***		3.59***	3.67*	3.04***		3.90**
	H				3.90**	4.04***				3.93***		3.99***	3.88*	4.37***		3.65**
	T				3.76**	3.78***				3.76***		3.76***	3.78*	3.77***		3.77**
Route Change (F14)	L									2.34*		2.27***	2.49*	2.26**	1.81***	2.30*
	H									2.54*		2.55***	2.29*	2.48**	2.93***	2.50*
	T									2.45*		2.39***	2.38*	2.38**	2.40***	2.41*
Route Complexity (F15)	L		3.83***	2.88**									3.09**			2.30***
	H		4.21***	3.13**									2.85**			3.58***
	T		4.02***	3.00**									2.97**			2.99***

* Significant at *p* < .1, ** significant at *p* < .05, *** significant at *p* < .01,

Table 13: differences in means on factors obtained from EFA for respondents with high/low scores on the factors.

			Total direct effect	**Total Indirect effect**	**Total effect**
Complexity	→	*COP Decisions Centrality*	−.65	(.25)(.17) = .04	−.61
Information availability	→	*COP Decisions Centrality*	.17		.17
Rate of change	→	*COP Decisions Centrality*		(.28){(−.65) + (.25)(.17) } = −.17	−.17
Complexity	→	*Planning decisions centrality*	.46	(.68) (−.61) = −.41	.05
Information availability	→	*Planning decisions centrality*		(.68) (.17)	.12
Rate of change	→	*Planning decisions centrality*		(.68) (.05)	.03
Rate of change	→	*Information availability*		(.28)(.25)	.07

Table 14: Total effects in the initial path model.

* Significant at $p < .1$, ** significant at $p < .05$

			Total direct effect	**Total Indirect effect**	**Total effect**
Product complexity	→	*COP Decisions Centrality*	.22**		.22**
Product complexity	→	*Planning decisions centrality*		(.22) (.31) + (.24) (−.15) = .03**	.03**
Supplier complexity	→	*Planning decisions centrality*	.21*	(.20) (−.15) = −.03**	.18*

Table 15: Total effect of product complexity and supplier complexity on the decision structure.

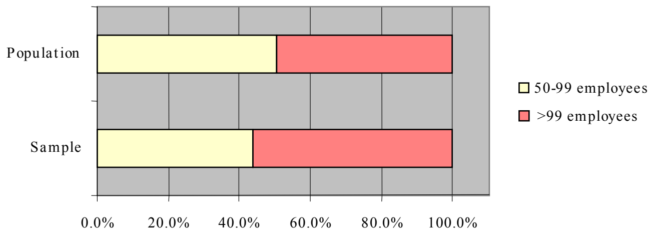

Figure 1: Comparison of sample and population with respect to number of employees (>50 employees).

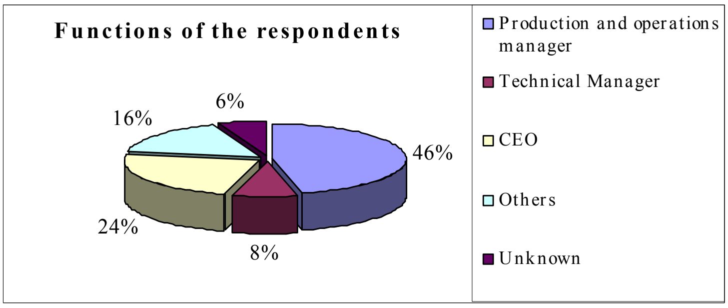

Figure 2: Functions of the respondents.

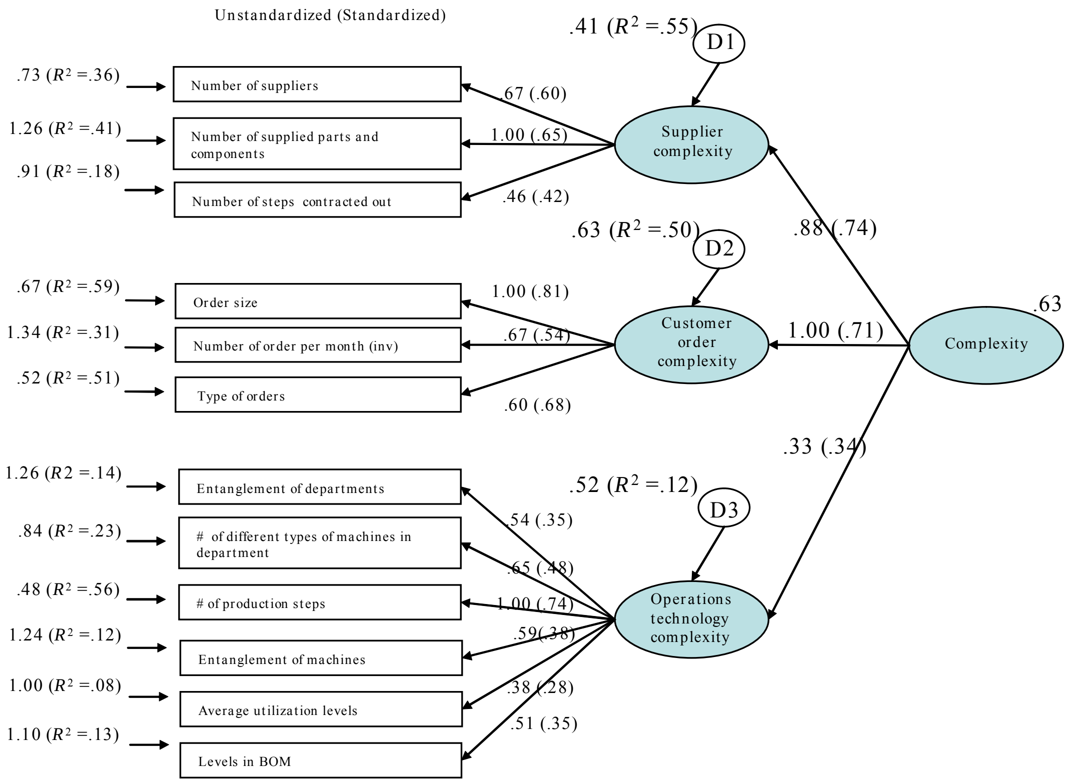

Figure 3: CFA model of the 2nd-order construct complexity.

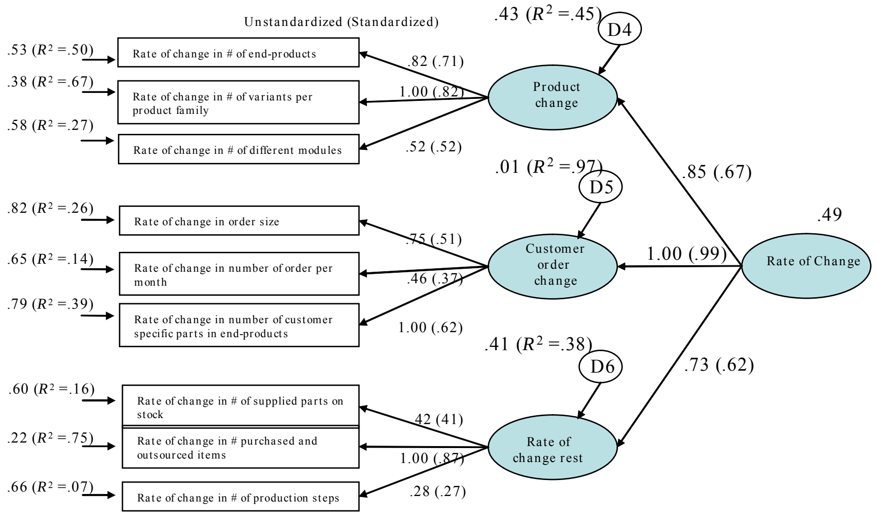

Figure 4: CFA model of the 2nd-order construct Rate of change.

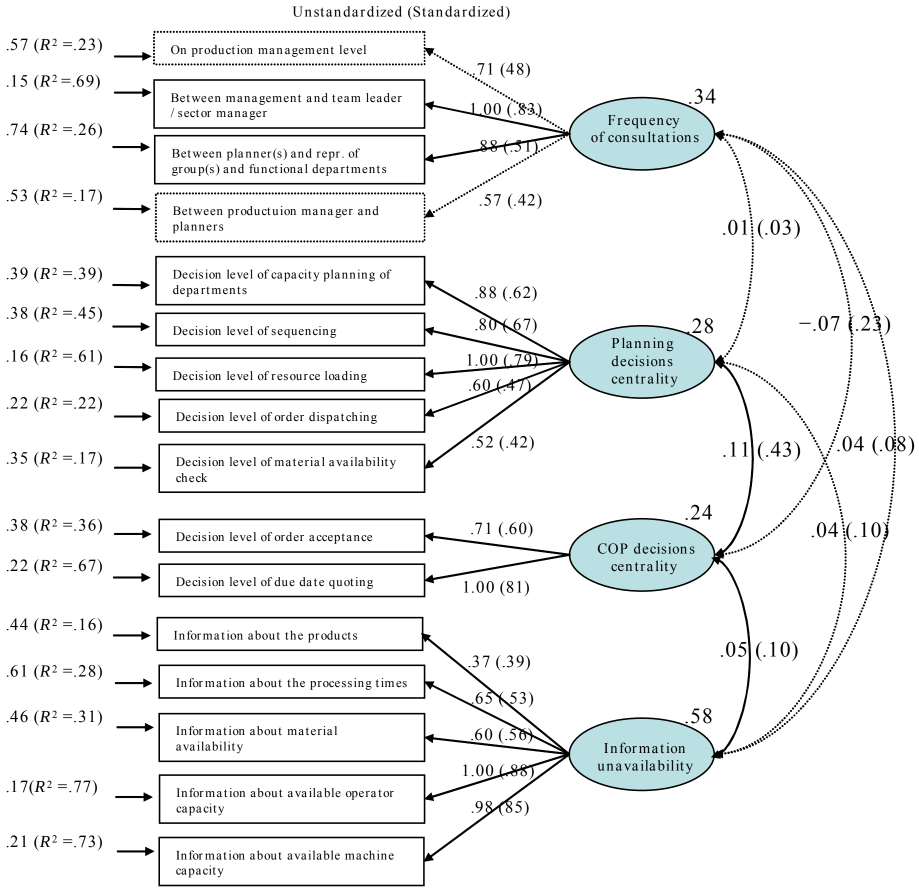

Figure 5: Measurement model of Control Requirements.

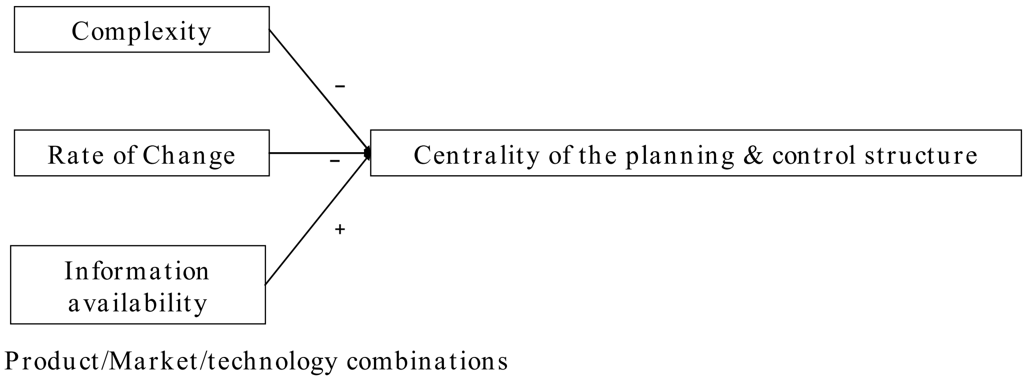

Figure 6: Adjusted proposition: the relation between *Complexity, Rate of change, Information availability* and *Centrality of the* production planning and control structure.

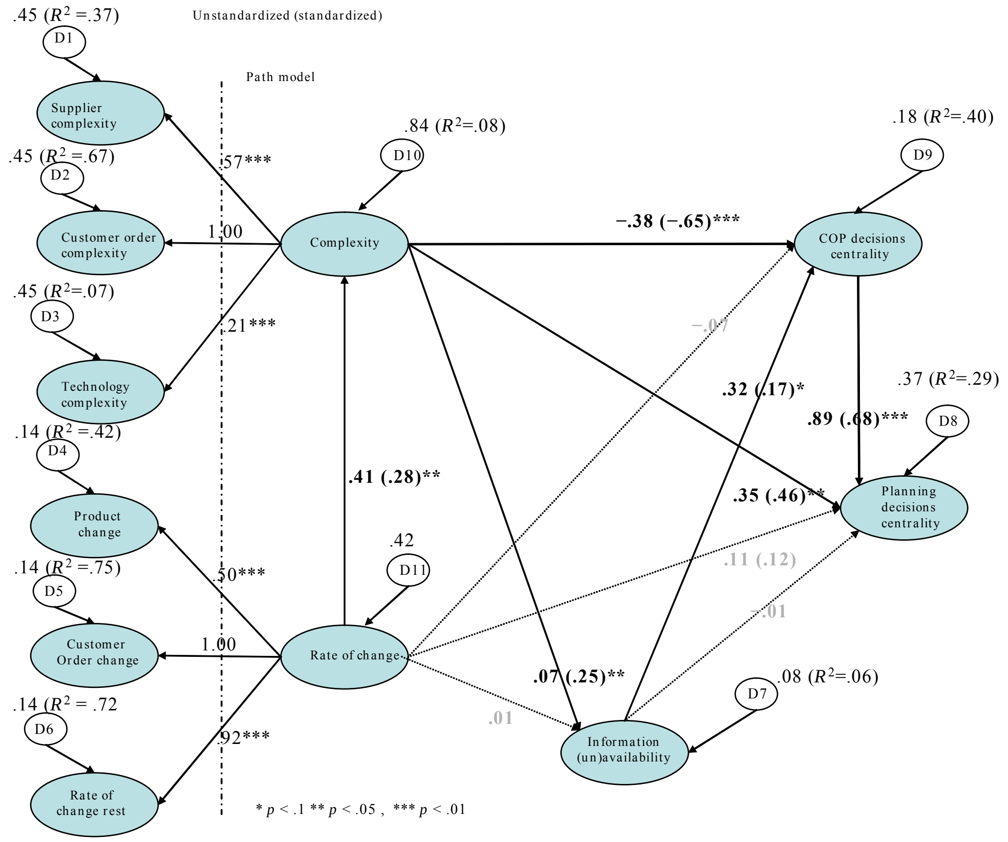

Figure 7: A structural model of Complexity, Rate of change, Information availability and Decision structure (d.f. = 487, χ^2 = 830.697, p_{model} = .000, CFI = .978, NFI = .949, TLI= .975, and RMSEA$_{[.052,.065]}$ = .059).

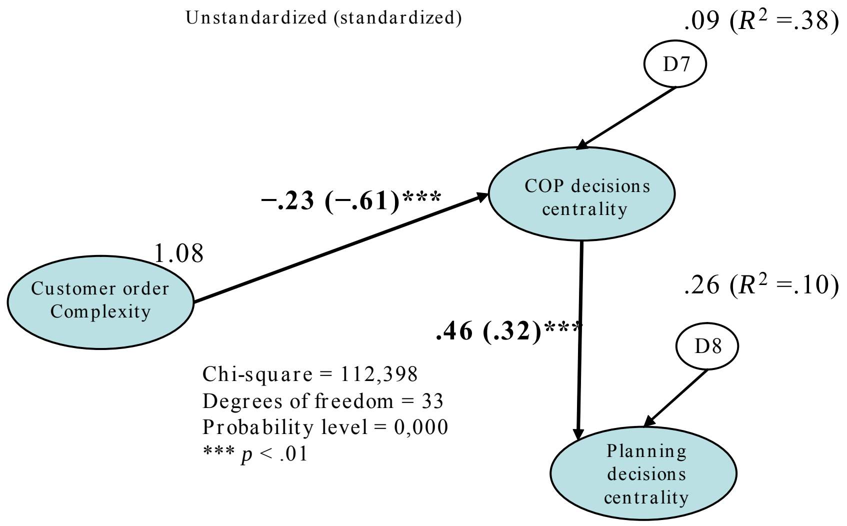

Figure 8: customer complexity as the cause for centrality.

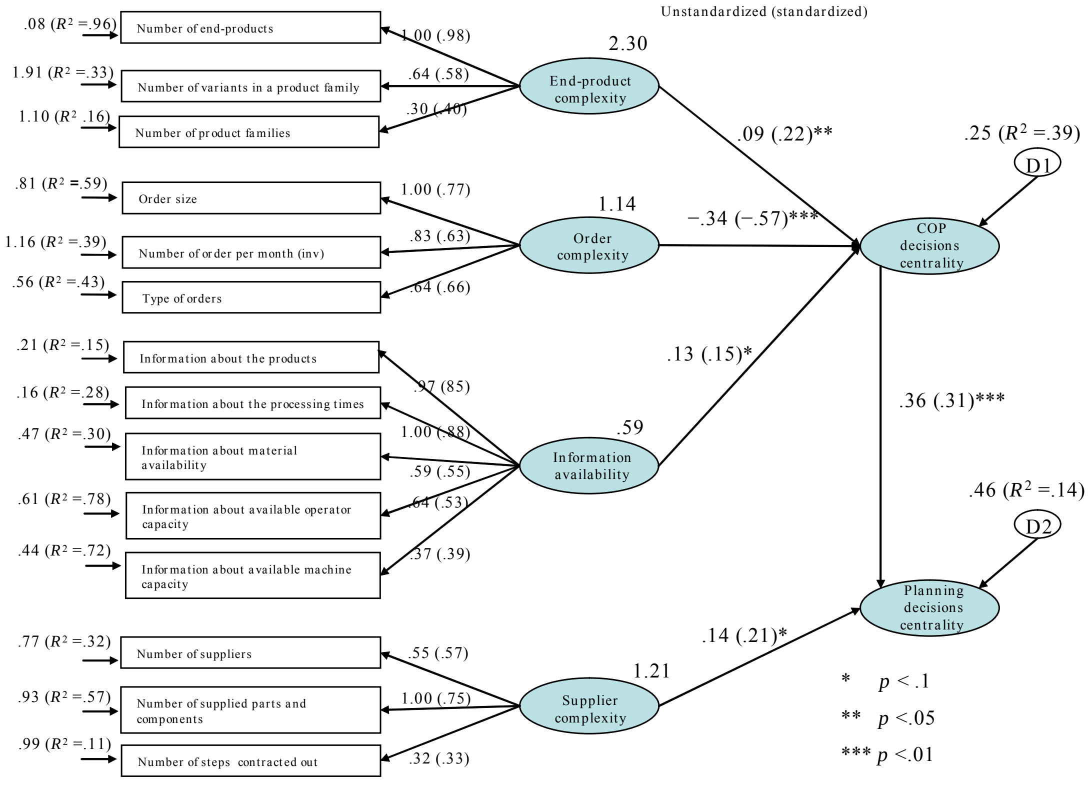

Figure 9: An alternative SEM model based on EFA factors.

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