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A case study

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Understanding the Impact of Non-standard Customisations in an Engineer-to-Order Context: A Case Study

Companies operating with an engineer-to-order (ETO) manufacturing strategy produce customised solutions for their customers. While they may be able to build on a base of existing sub-solutions, e.g. standard product structures, modules or parts when engineering a customer-specific solution, they often have to create something completely new to satisfy customers' requirements.

However, it is not always clear to ETO companies what the costs associated with making customer specific solutions are, or which product or project characteristics drive costs and in what business processes. Therefore, it is not clear to companies if it is actually profitable for them to fulfil all of their customers' requirements. Hence, making it relevant to understand how creating non-standard customisations impact project profitability.

This paper presents a framework for how ETO companies can quantify the impact of the complexity associated with non-standard customisations when cost data is only available at the project level. The framework is theoretically founded; it is based on statistical regression and a definition of a complexity index for non-standard customisations. The framework is validated in the context of an ETO case company and empirical data is presented.

Keywords: engineer to order; complexity analysis; Mass Customization; Impact analysis; Product Customisation

1. Introduction

As customers' demands and expectations for custom solutions grows, the relevance of operating strategies that support product customisations increases. Companies that employ an engineer-to-order (ETO) operating strategy are distinguished from those that use other strategies, such as make-to-order (MTO) , assemble-to-order (ATO), configure-to-order (CTO) or make-to-stock (MTS), by the finalization of the product design and specifications after the customer order is placed (Gosling and Naim 2009; Haug, Ladeby, and Edwards 2009; Rudberg and Wikner 2004; Hansen 2003).

Along the lines of Gosling and Naim (2009), Willner et al. (2016) and Wikner and Rudberg (2005), the present study takes the stand that, in an ETO company that employs strategies, such as mass customisation (Pine 1993), product platforms (Lehnerd and Meyer 2011) and product modularisation (Ulrich and Eppinger 2011), where some of the product design and engineering can be based on reuse of standard modules and parts. This enables ETO companies to operate in the span between two strategies: CTO and ETO.

The benefits of increased standardisation, in terms of defined standard product structures and standard modules, are well documented (Haug, Hvam, and Mortensen 2013; Hvam, Mortensen, and Riis 2008; Z. Wang et al. 2016; Kasiri et al. 2017). However, the downside of standardisation in ETO companies is the reduction of the solution space (Forza and Salvador 2008). For ETO companies, this results in reduced flexibility to fulfil customer requirements (Haug, Hvam, and Mortensen 2013), thus implying a product variety trade-off between market and operational performance as indicated by Um et al. (2017). From a strategic point of view, it is therefore not necessarily desirable for ETO companies to employ a strict CTO or mass customisation strategy because it would require them to reject some customer orders and, thus, lose sales. The following question should therefore be asked: What is the right balance between standard customisation (SC) vs. non-standard customisation (NSC)? Does the increased sales actually add value to a company? Or does the added complexity of creating the NSCs eat the profit margin? To support this discussion, it is relevant for ETO companies to understand the impact of NSCs on operational performance (Harbour 2009; Kaydos 1998), e.g. on project profitability. Therefore, the present research aims to help ETO companies understand how NSC affects the overall project profitability.

A bottom up/activity-based cost analysis can be used to determine the impact of NSC. However, this approach depends on the availability of detailed cost data and the distinction between SC and NSC in the cost data collected and measured. While data on material costs and routing costs may be available at a module level, other relevant cost data, such as engineering costs or project management, may not. ETO companies often calculate costs at the total product level (for the entire project), making it difficult to clarify which part of the cost is driven by the SC and which is driven by the NSC. Thus, the availability of cost data complicates the impact analysis, why an approach is needed that utilises cost data at the project level.

Based on a literature review, this paper presents a framework for how ETO companies can analyse the impact of NSC when cost data is only available at the project level. The approach is based on statistical cost estimation methods and the definition of a complexity index for NSC. The proposed framework is then validated within an ETO company that combines project sales of SC and NSC where cost data is represented on project level.

With this knowledge, ETO companies can define the complexity of their projects and NSCs, and they can improve their basis for projects decisions making.

1.1 Standard customisation vs. non-standard customisation in an ETO context

While there is no generally agreed upon definition of ETO companies in the literature (Gosling and Naim 2009), it is widely agreed that the customer order decoupling point (CODP) can be used to define the ETO operating strategy relative to other strategies, such as MTO, ATO, CTO or MTS (Gosling and Naim 2009; Haug, Ladeby, and Edwards 2009; Rudberg and Wikner 2004; Hansen 2003).

One of the discussion points in the literature is whether ETO companies cover only pure customisation, where a product is engineered from scratch after the customer has placed an order, or if a product can be partly based on a configuration of standard parts (Gosling and Naim 2009; Willner et al. 2016).

Within the traditional ETO CODP, Wikner and Rudberg (2005) define two types of CODP along the engineering dimension – ETO_{ED} and adapt-to-order (ATO_{ED}). Willner et al. (2016) present four types of ETO companies defined by the engineering complexity and the number of units sold: Complex ETO, Basic ETO, Repeatable ETO and Non-competitive ETO, in order to identify the appropriate level of standardisation and design automation for different ETO companies. In this way, they define ETO companies in broader terms rather than viewing them as pure customizers. The present study adopts the broader definitions of ETO companies, and in line with the types of customisations reported by Lampel and Mintzberg (1996) it applies the definitions proposed by Hansen (2003) for the engineering/design dimension of CODP. Hansen (2003) distinguishes between different customer entry points, as selecting a variant, CTO, modify-to-order (MTO) and ETO, where standard products, standard parts/modules, a generic product structure or design norms and standards, respectively, are defined at the time of customer entry (Figure 1).

Figure 1. Types of engineering strategies (adopted from Hansen 2003)

The present study argues that an ETO company does not necessarily fall into one of these engineering dimension categories (CTO, MTO or ETO), but it can operate within the range and, even within the same ETO product/project, different CTO, MTO and ETO elements can be applied. Using an example of an ETO company that produces cement plants, a plant will be partly based on a configuration of standard modules chosen to fit the output rate and size (CTO); it will contain parts or modules modified to meet the geological conditions of the plant location (MTO) and it may require completely new solutions in order to support the customers' requirements (ETO).

In this way, the present study argues that an ETO project/product can contain both standard modules/parts as well as modified and completely new modules/parts, i.e. SC and NSC, respectively (Figure 2).

Figure 2. Standard customisation (SC) and Non-standard customisation (NSC)

2. Impact of Customisation in an ETO Context: A Literature Review

The impact of product variety or level of product customisation on operational performance is a topic that has received some attention in the literature (Squire et al. 2009; Yee 2005; Zhang, Chen, and Ma 2007; Brunoe and Nielsen 2016; Wan, Evers, and Dresner 2012; Berry and Cooper 1999; Park and Okudan Kremer 2015; ElMaraghy et al. 2013; Wang et al. 2011). Generally, highlighting the negative impact of product variety or the level of customisation, different authors have analysed the performance impact of alternative strategies to manage variety or customisation (Um et al. 2017), such as mass customisation (Liu, Shah, and Babakus 2012; Kumar, Nottestad, and Macklin 2007), product platforms and modularisation (Tu et al. 2004; Aljorephani and Elmaraghy 2016; ElMaraghy et al. 2013; Medini 2015), postponement of product differentiation (Forza, Salvador, and Trentin 2008; Su et al. 2010; Ngniatedema, Fono, and Mbondo 2015) and postponement of the CODP (Kumar, Nottestad, and Macklin 2007; Jiang and Geunes 2006).

However, the majority of previous studies have explored the impact of product variety or level of customizations on operational performance in the context of mass producing companies moving towards more customized product portfolio. Only few studies have examined the performance impact of ETO companies moving towards CTO setup or mass customisation (e.g., Bonev and Hvam 2013; Ulrikkeholm and Hvam 2014).

Bonev and Hvam (2013) define the performance measures that are relevant for planning strategic actions for mass customisation operations in an ETO context. They highlight the contribution margin relative to revenue as such a measure. Within a mass customisation context, Ulrikkeholm and Hvam (2014) analyse the impact of product variety at the module level, showing that even with a modular product structure, product variety comes at a cost.

While many of the previous studies highlighted in this section investigate generalizable relationships between product variety/level of customisation and operational performance, only a few present tools or frameworks that can help companies analyse their own performance or facilitate decision making. Liu et al. (2012) help facilitate the decision about which market or environmental conditions are appropriate for mass customisation; however, the decision is based on generalised data, not on the performance analysis of an individual company. Myrodia and Hvam (2014) present a performance analysis method for CTO product portfolios; however, they stay at the product line level and they do not assess profitability at the feature/solution level. Hu et al. (2008) propose a unified measure of complexity for product variety and assembly process that allows for finding the optimal assembly supply chain. Hu et al. (2011) further elaborate on how the operations of assembly systems can be used as a way to support product variety. Kumar and Stecke (2007) present and utilise the mass customisation and personalisation effectiveness index (MCPEI) to measure the effectiveness of a mass customisation and personalisation strategy.

Within the context of mass producers moving towards mass customisation, Spahi and Hosni (2008) define a model for finding the optimal level of product customisation based on a number of strategic goals. They identify a way to determine the level of customisation, not in terms of the CODP, but as a measure of how many distinct product variants can be produced by combining the product features or the module options. While the purpose of their study is comparable to the aims of the present study, the context and definition of customisation level make their approach difficult to adopt here.

Hegde et al. (2005) define and test a statistical regression model for determining the optimal level of customisation with respect to the probability of failures. The model takes into consideration the product complexity and level of customisation of individual design-to-order products. While the overall analysis method is interesting, the measure of the level of customisation is not considered appropriate for the current study's analysis. As the level of customisation is measured as the number of design/functional parameters set by the customer relative to the total number of parameters (Hegde et al. 2005). However, in an ETO context, where elements of pure customisation are possible, it can be difficult to define the total number of parameters.

Based on a literature search of Scopus, with the search terms (profit* OR impact OR performance) AND (ETO OR "engineer to order" OR MTO OR "make to order" OR "mass customization" OR customiz*), to the best of our knowledge analysis of the operational impact on the profitability and cost of NSC complexity in an ETO context has not been sufficiently analysed in the literature. From the reviewed literature, statistical regression is identified as a relevant impact analysis tool. However, how the distinction between SC and NSC can be represented in this type of regression model needs to be further investigated.

3. Research Method and Framework Definition

In order to analyse the impact that creating NSCs in an ETO context has on profitability, the present study proposes a three-step framework: Step 1: Identify the relevant complexity drivers at the project level and NSC level; Step 2: Define a complexity index for NSC and Step 3: Develop impact model. The framework is theoretically grounded, and it is based on statistical regression (e.g. Caputo and Pelagagge 2008; Brunoe and Nielsen 2012; Wan, Evers, and Dresner 2012; Berry and Cooper 1999; Hegde et al. 2005) and the definition of a complexity index (e.g., Bearden 2003; Budde, Nagler, and Friedli 2015). In the following sections, the theoretical background for the framework will be presented, the basic statistical model of the framework will be defined and the individual steps of the framework will be described. In order to test the applicability of the framework, a case study in an ETO context is presented along with empirical data of the NSC impact.

3.1 Theoretical background of the framework

3.1.1 Statistical regression for impact analysis

To the best of our knowledge, analysis of the operational impact of creating NSCs in an ETO context has not been sufficiently addressed in the literature. However, in a mass production context, Wan et al. (2012) and Berry and Cooper (1999) use statistical regression to analyse the impact of product variety on operational performance.

Statistical regression is also a well-known tool in quantitative parametric cost estimation models, and it has been applied in an ETO context (Caputo and Pelagagge 2008; Brunoe and Nielsen 2012). Parametric cost estimation methods are function-based; they identify the relationships between cost and functional parameters/product attributes, also referred to as cost drivers, and they can utilise historical data and statistical regression to define the exact relationship that is representative of a specific product family (Foussier 2006b; Niazi et al. 2006). Thus, statistical regression is seen to be an appropriate estimation tool in the early product lifecycles (Stewart, Wyskida, and Johannes 1995) or in an ETO context when the detailed design is unavailable (Caputo and Pelagagge 2008). These characteristics make it a more suitable approach for the purpose of this paper as opposed to a bottom up/activity-based cost analysis, an approach that depends on the availability of detailed cost data and a distinction between SC and NSC cost data within a project.

3.1.2 Complexity quantification and measure

In cost estimation regression models, specific product features or measures are defined as cost drivers (independent variables). In the case of a pressure vessel, these could include: vessel volume, external surface size and weight. Because the present study focuses on NSCs in an ETO context, thus indicating a large variation in the types of solutions and complexity, it is difficult to define product measures or features that are represented as key cost drivers over the full spectra of solutions. Therefore, a common measure or cost driver must be defined that can represent the complexity of the different NSCs in the statistical regression model.

To overcome this obstacle, the study explored complexity measures and complexity index theory (Bearden 2003), because complexity is generally understood to impact operational performance (Park and Okudan Kremer 2015). The complexity index was introduced by Bearden (2003) as a broad representation of a system in order to compare and assess the risk related to complex satellite projects. By defining a complexity index, Bearden (2003) is able to compare the complexity of different satellite projects and define development time and cost as a direct function of project complexity.

Bearden (2003) presents a three-step process for defining a complexity index: (1) identify the parameters that drive complexity, (2) quantify the identified parameters and (3) combine the parameters into an aggregate complexity index. Filippazzo (2006) utilises the complexity index theory to develop a parametric time and cost estimation model for satellites. Banazadeh and Jafari (2012) have developed a heuristic complexity-based method for cost estimation of aerospace systems. Budde et al. (2015) define a complexity index for improved decision-making between different design alternatives. They apply steps similar to those proposed by Bearden (2003); however, they provide concrete tools that can be used to analyse interdependency and assign complexity values to the complexity drivers. Ramani and Venkatraman (1991) define a complexity index for improved decision making and utilise stepwise regression analysis to identify significant independent variables to be included in the index.

While there is no generally accepted definition of complexity (Park and Okudan Kremer 2015), many researchers have contributed to defining measures for complexity (Sun et al. 2015; Summers and Shah 2010; Suh 2005). Samy and ElMaraghy (2010) define a general complexity measure for product assembly that addresses complexity at the product level based on a summation of the complexity of individual parts. Grabenstetter and Usher (2013) define a complexity equation, including a number of complexity drivers, to determine job complexity in an ETO environment for due-date estimation using statistical regression to prove the significance of the included complexity drivers. The present study does not attempt to define a generalizable complexity measure, which is why an in-depth review will not be presented. As the definition and measures of complexity are highly related to context (Samy and ElMaraghy 2010), the present study proposes an NSC complexity measure, specific to the organisation being analysed, based on the complexity index theory (Bearden 2003; Budde, Nagler, and Friedli 2015).

3.2 Statistical regression model

The present study proposes the use of statistical regression to identify the impact of

NSC, in combination with the definition of a complexity index, as a measure of NSC complexity. A basic regression model can be defined as expressed in Equation (1):

$$X_{Project} = \beta_0 + \beta_1 * \sum_0^n C_{NSC} \quad (1)$$

Where $X_{project}$ is the project performance or cost measure, C_{NSC} is the complexity measure of an individual NSC in the project and n is the number of NSCs in the project.

However, this model does not take into consideration that other project-related complexity drivers can influence project costs or performance (e.g. the complexity of the standard solution, process or organisational complexity drivers). Thus, there is a need to moderate the model with project-related complexity drivers, as seen below in Equation (2):

$$X_{Project} = \beta_0 + \beta_1 * PC_1 + \beta_2 * PC_2 + \cdots .. \beta_x * PC_x + \beta_{x+1} * \sum_0^n C_{NSC} \quad (2)$$

Where PC_x is the project complexity drivers.

The regression model presented in Equation (2) is considered to be the basic model that represents the logic of the framework presented in the present study. However, the later statistical analysis may reveal that certain variables have a non-linear contribution or they may prove to be insignificant. This will be discussed in Section 3.4 (Step 3 of the framework).

By defining Equation (2), the complexity of NSC is considered to be a variable in the overall complexity of an ETO project, and project performance is defined as a function of the project complexity.

3.3 Framework Step 1: Identify the relevant complexity drivers at the project and NSC levels

The purpose of this step is to identify the ETO project/product features or variables that drive complexity and, thus, impact operational performance i.e. to identify complexity drivers, sometimes referred to as complexity factors (Vogel and Lasch 2016). As indicated in the previous section, complexity drivers at both the project level and the NSC level should be identified.

Identification of complexity drivers is a complex process in itself and a research area well covered in the literature (e.g., Vogel and Lasch 2016; Budde, Nagler, and Friedli 2015). In this process, the present study will therefore merely refer to previous research studies that have proved useful. It is recommend to identify the complexity drivers based on stakeholder interviews with process experts (Vogel and Lasch 2016; Budde, Nagler, and Friedli 2015) across functions in order to obtain a cross-organisational perspective. Asking the question; what factor that drive complexity and cost in projects? Three dimensions should be considered when identifying complexity drivers: product, process and organisational complexity (Wilson and Perumal 2009). Quantity, diversity and the interrelationship of elements in the product design are some generally accepted product complexity drivers that can be considered (Park and Okudan Kremer 2015). While the present study is based on the understanding that complexity drivers are highly context-related, we have found inspiration from previous research studies. Toward that end, several studies have been useful. Grabenstetter and Usher (2013) highlight a number of complexity factors relevant to the ETO context and Myrodia & Hvam (2015) and Vogel and Lasch (2016) present a literature review of the complexity factors/drivers relevant to manufacturing companies.

3.4 Step 2: Define a complexity index for NSC

The complexity of NSCs in an ETO product is defined as the sum of the complexity of individual NSCs as indicated in the definition of the statistical model (Section 3.2), in line with the complexity definition by Samy and ElMaraghy (2010). Therefore, the purpose of this step is to define a complexity index for a specific NSC. The complexity drivers at the NSC level identified in the first step should be evaluated in terms of their appropriateness for inclusion in the complexity index. Thus, different considerations should be taken into account: (1) data availability in the early quotation phase (Grabenstetter and Usher 2013), (2) the correlation between drivers (Bearden 2003; Budde, Nagler, and Friedli 2015) and (3) applicability across all NSC (meaning that solution-specific features should not be included). For the complexity drivers that are discrete variables, a complexity value is assigned based on choices, e.g. size may be a continuous parameter represented by a number of parts, in which case there is no need to assign a value. However, to determine the parameter in the early quotation phase, a discrete parameter could be more appropriate (for example, size represented by a part, a unit or a module). In this case, a complexity value must be assigned to each choice for inclusion in the complexity index.

Complexity drivers can now be combined into a complexity index. This may be as simple as adding the values for the included complexity drivers together or more complicated equations with an individual weighting of the drivers. The definition of the complexity index is very dependent on stakeholder input, and it may be defined as an iterative process to define a complexity index that gives an appropriate representation of the solution complexity. It is recommended to define the complexity index in workshops with key stakeholders. And in these test the complexity index values on a number of NSC with a variation in complexity, to ensure that the index represents and differentiate the complexity appropriately.

The complexity index should be normalised relative to the minimum and maximum value to arrive at a complexity index expressed as a percentage, ranging between 0 and 1. By doing so, the gap between projects with no NSC and projects with a few low complexity NSCs is closed.

3.5 Step 3: Develop impact model

The purpose of Step 3 is to analyze the impact of the identified complexity drivers on the relevant operational performance indicators using multiple regression analysis. The basic regression model was defined in Section 3.2 and presented in Equation (2). In this step, the model best representing the available data set is identified in order to analyse the impact (Grabenstetter and Usher 2013) of the NSC complexity on operational performance. First, the project level complexity drivers must be evaluated for their appropriateness of being included in the model. The same considerations apply, as to the NSC level complexity drivers. Then, the data set for the statistical regression must be prepared by: (1) assigning complexity values to all the included complexity drivers, (2) calculating the complexity indexes for all NSCs, (3) checking for missing or faulty data and (4) checking the dependent variables for inter-correlation (Foussier 2006a).

Statistical regression can now be conducted on the dataset for relevant dependent and independent variables. Different models can be tested, and insignificant dependent variables can be reduced from the model to identify the most appropriate model (Stewart, Wyskida, and Johannes 1995; Ramani and Venkatraman 1991). From the final regression model, the complexity drivers that actually have a significant impact on the performance indicators can be identified and the impact can be quantified.

4. The Case Study

Nilpeter A/S is a family-owned Danish manufacturing company that produces customised printing presses for label and package materials (Figure 3).

Figure 3. Nilpeter label press. Build of modules each with an individual print technology or processing step.

The company currently has a number of different product lines to support different markets, different printing technologies and different end-customer industries.

The product families are very modular at a high level (see Figure 3), with one print technology or processing step per module, meaning that customers can configure their printing press with different print technologies. However, many customisations are made at a lower product level, that is, customisations of the individual printing modules. At the lower product level, there is less modularity, and customisations are more dependent on engineering development.

Nilpeter has a sales catalogue with standard modules and units from which standard customisations can be made. Within the standard solution, the company has a basic press (a minimum configuration) and offers standard add-on/optional solutions. This represent the CTO part of the company's offerings. Customers can further request non-standard solutions, which require engineering involvement. In this way, the printing press is customized with a combination of SC and NSC and thus representing both CTO and ETO solutions see Figure 4.

Figure 4. The case company's modular product structure, each lable press is build up from basis modules, Optional add-on modules and Non-standard modules.

Nilpeter's customers need flexibility in their printing presses to support multiple label customers with a variety of printing needs. The highly customised solutions are one of the company's key competitive advantages in the market; therefore, customisation is a strategic decision. While the flexibility in Nilpeter's solution space is not something the company is willing to compromise, it still aims at being more efficient in providing customised solutions. Nilpeter is aware that catering to specific customer needs adds complexity costs to the organisation, product assortment and supply chain. However, the exact impact of making NSCs is not known. While the company experiences a high variance in its project profitability, it cannot immediately detect the relationship between NSCs and profitability because the complexity of these can vary significantly, just as the complexity in the configuration of the standard solution can vary. In order to improve its cost estimation of NCSs, and facilitate the discussions of certain projects should be rejected the company needs to be able to define the complexity of the projects as well as understand the concrete impact on the organisation's profitability.

The company measures cost on a project level (e.g. cost of the engineering hours, final assembly costs, test costs and installation costs). The only cost that is calculated on a part or module basis is the material and routing cost. This makes it difficult to distinguish between the cost of non-standard and standard solutions; thus, it complicates the cost and impacts analysis of supplying NSCs to its customers. This highlights why an alternative to a bottom-up cost analysis method is needed.

In this case study, all projects for one product line were analysed, including all the supplied NSCs related to the projects. This entailed a total of 68 projects and 238 NSCs. The following sections will describe the findings from applying the proposed framework at the case company.

4.1 Step 1: Identify the complexity drivers at the project and NSC levels

To obtain a cross-organisational perspective of complexity drivers, a total of eight semi-structured interviews were conducted across the organisation with representatives from the Finance, Sales, Order Handling, Engineering, Production and After Sales departments. With the ETO relevant complexity drivers as defined by Grabenstetter and Usher (2013) in mind, the interviews revealed a number of complexity drivers. Some had emphasis from across the organisation e.g. late changes to customer requirements. Other drivers were more department-specific, such as communication between employees in the Engineering Department and the Original Equipment Manufacturer (OEM) suppliers regarding OEM part specifications. Table 1 presents a summary of the complexity drivers identified during the interviews, both on project level and on NSC level. The complexity driver discussed in the literature by Grabenstetter and Usher (2013) are used as an inspiration – a reference is provided for each of the complexity drivers identified in the case company.

Table 1. Complexity drivers at the project and NSC levels

4.2 Step 2: Define a complexity index for NSC

The complexity drivers at the NSC level identified in the first step were evaluated in terms of their appropriateness for inclusion in the complexity index, as discussed in Section 3.4. Comments for disregarded drivers are mentioned in Table 1. This led to including four drivers in the complexity index for the NSCs: size of NSC, integration level, solution type and maturity.

Based on information obtained from the conducted interviews and feedback from stakeholders, the complexity drivers were weighted and then divided into relevant sub-factors (e.g., size of the NSC was divided into part, sub-assembly, unit or full module) The sub-factors were assigned to all previously supplied NSCs relevant to the projects in the dataset (a total of 238 NSCs). Because all the complexity drivers were categorical, the complexity was quantified and a value was assigned to each sub-factor, ranging from 1 to 10. This process was conducted in a number of iterations to identify the most appropriate complexity index to differentiate and represent the complexity of different types of NSCs. The final complexity driver weighting and complexity values are presented in Table 1, and are represented by the following formula:

$$C_{NSC} = 2 * Size\ of\ the\ NSC + 4 * Integration\ Level + Maturity * Solution\ type \qquad (3)$$

Where: $\text{Size of the NSC} = \{4,5,6,7\}$, $\text{Integration Level} = \{1,6,10\}$, $\text{Maturity} = \{5,2,1\}$, $\text{Solution type} = \{1,4,7,10\}$.

With the defined complexity index, minimum and maximum complexity values are 13 and 104 that can be assigned to the NSC. This was normalised to values expressed as a percentage ranging between 0 and 1.

4.3 Step 3: Develop impact model

A multiple regression equations was defined that included both the complexity index for NSCs and the moderating factors of the general project complexity, as identified in Step 1 (Table 1). Similar to the NSC level complexity drivers, the project level drivers were evaluated in terms of inter-correlation, data availability at the time of the quotation and data availability for the historical dataset. Comments about the disregarded drivers are presented in Table 1. Evaluation led to disregarding two factors, leaving the following factors in the regression equation: Size (S), Level of standard configuration (LSC), Basic solution/Product line maturity (BM), Add-on solution maturity (AM) and the Complexity of NSC (C_{NSC}):

$$X_{Project} = \beta_0 + \beta_1 * S + \beta_2 * LSC + \beta_3 * BM + \beta_4 * AM + \beta_5 * \sum_0^n C_{NSC} \quad (4)$$

The setup regression equation was then statistically analysed using: project profit (relative contribution margin [%]) as the dependent variable. A number of different regression models were tested to determine the optimal model, and the model was reduced to exclude the insignificant independent variables. The statistical results for the final model are presented in Table 2. To maintain the company's confidentiality, the intercept in model 1 has been blanked.

Table 2. Regression Model Results

4.5 Case results

The model is significant and is able to reject the 0-hypothesis (i.e. that NSC have no impact the profitability). Generally, all the insignificant independent variables were reduced from the model, except in the case of sqrt (NSC), where the variable was not directly insignificant and where the overall quality of the model was higher if included.

The complexity drivers that proved to be significant were: Size (S), Basic solution/Product line maturity (BM) and Complexity of NSC (C_{NSC}).

$$Profit_{Project} = \beta_0 + \beta_1 * \ln(S) + \beta_3 * \ln(BM) - \beta_5 * \sqrt{\sum_0^n C_{NSC}} \qquad (5)$$

The dependent variables that were insignificant and removed from the model were: Level of standard configuration (LSC) and Add-on solution maturity (AM); however, in the interviews with stakeholders these were considered to be important complexity drivers. This may indicate that the measures applied for these were inappropriate and could be improved to show a significant impact.

Impact of NSCs on profit

Model 1 shows that NSCs have a negative impact on a project's profit. This is in line with the expected results, as preliminary studies in the company showed that many NSCs are sold at prices that barely cover their material costs. With values for $\sum_0^n C_{NSC}$ ranging between 0 and 7 in the analysed projects, the statistical results show a profit impact of NSCs ranging between -0% and –3%.

4.6 Case Model Test

To ensure that the produced regression model developed based on the framework actually improves predictions of profitability a test was performed using three ETO projects at the company. All three projects were conducted in parallel or after the analysis presented above, and are therefore not part of the data set the model was developed based on. The characteristics of the three test projects are presented in Table 3.

	Test Project 1.	Test Project 2.	Test Project 3.
Customer Destination	Croatia	Spain	Australia
Number of modules (Size)	30	15	30
Basic Maturity (BM)	70	71	72
Number of different NSCs	2	3	0
Normalized complexity index	0,59341	0,8022	0

Table 3. The characteristics of the three test projects

The predicted project profit by the regression model was compared with the companies own pre-calculation as well as the actual realized profit. The case company does pre-calculations of project profit based on standard sales prices and cost prices on all standard modules and services. For NSCs sales the cost prices are estimated by expert experience and thus the profitability depends on the accuracy of these estimations. The results are presented in Figure 5 show that the accuracy of the method profitability predictions is better than the case companies current method in two out of three projects with an absolute error average of 3% against and 9,7%.

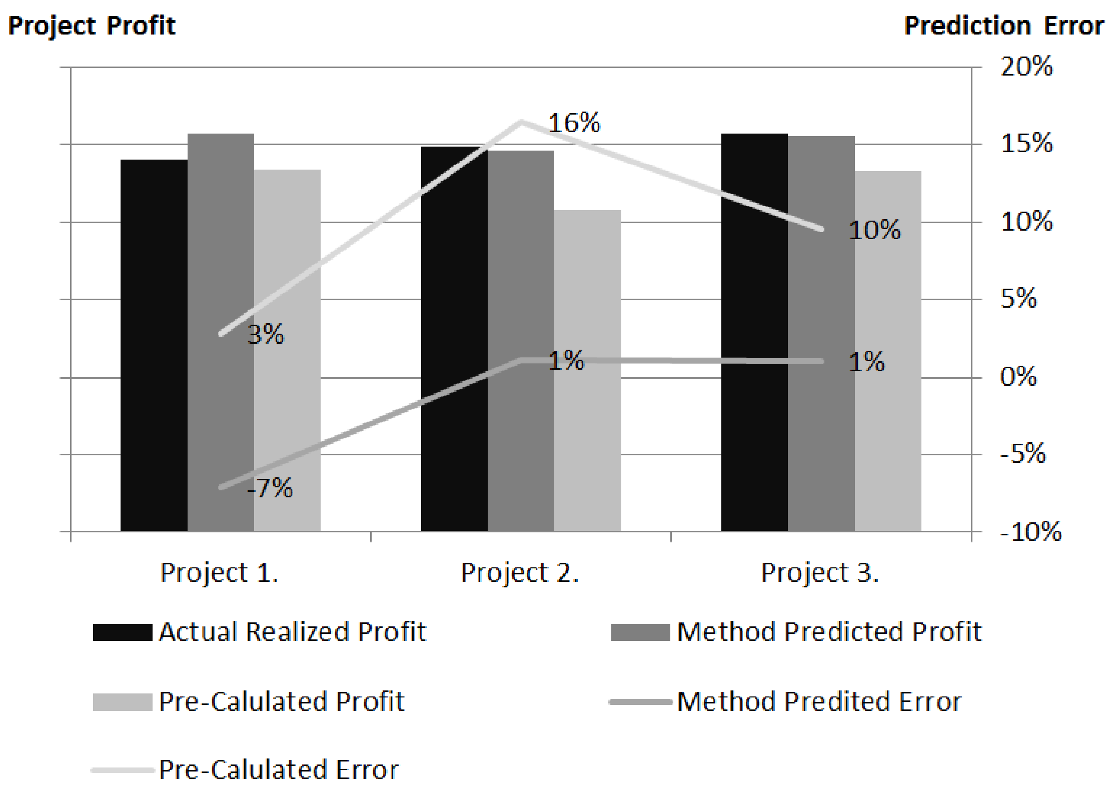

Figure 5. Regression Model test with three test projects

5. Discussion

It is not always clear to ETO companies what the costs associated with making customer specific solutions are, and therefore not always clear if it is actually profitable. Hence, making it relevant to understand how creating NSC impacts the overall project profitability. While a bottom-up costing approach would be the most accurate approach to analyse the impact of making NSC, this is not always possible because of data availability; it would require the company to clearly distinguish their cost data on a module /part level. ETO companies often calculate cost at the project level, making it difficult to clarify which part of the cost is driven by the SC and which is driven by the NSC.

The use of the proposed framework in an ETO case company confirmed that a bottom-up costing approach to analyse the impact of NSCs is not always useful in terms of data availability. However, historical data at the project level was available, so the alternative statistical regression approach presented in the present study is viable.

The literature review generally revealed statistical regression analysis as an appropriate tool for impact analysis (e.g., Caputo and Pelagagge 2008; Brunoe and Nielsen 2012; Wan et al. 2012; Berry and Cooper 1999); it was used to analyse the relations between product variety or level of customization and operational performance. However, from the literature, it was not clear how the distinction between SC and NSC could be represented in the statistical regression model or how the complexity variation in the solution space of NSC could be captured. The present study contributes to the literature by illustrating how ETO companies can define a context-specific complexity index (e.g., Bearden 2003; Budde, Nagler, and Friedli 2015) for NSCs and apply this as an independent variable in statistical regression and the definition of a complexity index

To further validate the framework, the developed regression model based on the proposed framework in the article was tested in its effectiveness of predicting project profitability. Based on three test- projects the profit rate predicted by the regression model was compared to the realized project profit and to the company's current pre-calculation approach – where the estimations of the NSC are determined by experts within the company. The results showed improved profit predictability with the developed regression model; with an absolute average error of 3% compared to 9,7%. For one test project is the error of the model predicted profit higher than the companies pre-calculation. However, with an absolute average error of only 3% the regression model is considered to be effective in predicting project profitability and thus the presented framework is considered to be a valid approach.

The case company has expressed the relevance of the framework for the analysis of NSC impact and for comparing the complexity of different NSC with the defined complexity index. This should enable the company in improving the profitability of the projects executed by the company – by having an increased ability to analyse the impact of responding to highly specialized customer requirements with NSCs.

The quality of the regression model and the complexity index is highly dependent on the identification of relevant complexity drivers. This highlights the importance of finding the most relevant complexity drivers both on project and NSC levels. In this study it is recommended to increase the chance of success that the complexity drivers are founded in literature, as well as, based expert opinions.

The case company Nilpeter A/S is considered to be a representative example of an ETO company working in the span between CTO and ETO, with a solution mix of standard, modified modules/parts and pure customisations. The limitation of single case validation can affect the validity and reliability of research findings as single case studies may lead to findings that are too narrow in their application (Eisenhardt 1989). However, for the present study, single case validation is considered sufficient for putting forth a theoretically founded framework, since the study does not attempt to define a generalizable complexity measure or a generalizable relationship between NSCs and operational performance.

6. Conclusion

The present study proposes a theory-grounded framework to analyse the impact of NSCs on operational performance in an ETO context. The framework is based on statistical regression (Stewart, Wyskida, and Johannes 1995) of historical performance data as an alternative to a data-extensive bottom-up cost analysis, where a cost differentiation between SC costs and NSC costs would be required. A definition of a complexity index (Bearden 2003; Budde, Nagler, and Friedli 2015) for NSCs is utilised to create a measure that can comprehend the solution space of NSCs in an ETO context and represent the complexity in a statistical regression model.

The framework was validated in the context of an ETO case company that manufactures printing presses for labelling, and empirical data was presented. The impact of 238 NSCs in 68 projects on one performance indicator (project profit), was analysed. The statistical case results showed that NSCs will reduce profit by 0–3%. While the statistical case results are not generalizable, they are in line the findings reported in previous research, in the sense that an increase in the customisation level has a negative impact on operational performance (Squire et al. 2009; Ulrikkeholm and Hvam 2014; Park and Okudan Kremer 2015). A test of the case specific estimation model on three projects showed improved profit predictability compared to the case company's current estimation approach.

The framework presented in the article highlights the impact of NSCs on relevant performance indicators; thus, it provides ETO companies with quantitative input to their discussions about NSCs orders acceptance and how to price them to make up for the expected cost increase and profit loss. Thus, the improved knowledge can facilitate better decision making, higher project profit and profit predictability. Furthermore, the definition of an NSC complexity index will give ETO companies a comparable measure they can use to capture the span of the NSC solution space and the related complexity.

Future research in this area would include further validation of the framework in ETO companies in different industries to ensure the applicability and availability of the data and, moreover to test the method on a variety of different performance indicators.

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