Effectiveness of the Product Configuration Task: 
Theory Formalization and Test

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ABSTRACT

Quick and reliable response to customers’ needs has been argued to be a key competitive advantage when manufacturing customized products. Anecdotal evidence and case-based research point to the importance of the effective management of information on feasible product configurations in order to achieve good responsiveness. However, no empirical, large-sample test of this contention has been done as yet. Our paper begins to close this research gap by testing a theory-derived model of how information relating to product configuration determines the responsiveness in serving customers. We find that availability of information supporting the product configuration task indeed allows companies to serve their clients faster and more accurately. We also find these benefits to be mediated by the availability to learn from past product configurations.

Keywords: Product Configuration, Survey Research, Information Management, Knowledge Management, Product Variety Management
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1. Introduction

Increasingly, firms are relying on product configuration in order to promptly meet more and more diverse customers’ needs, thus overcoming what has been dubbed as the “customization-responsiveness squeeze” (McCutcheon et al. 1994). Companies such as Dell Computers and Cisco literally built their business model and success around their product configuration capabilities (Megretta 1998, Tseng and Piller 2003). Many other companies followed, making product configuration so ubiquitous nowadays that we take for granted the possibility to purchase configured cars, vacation packages, insurance arrangements, and other goods and services.

Surprisingly, Operations Management has not devoted substantial efforts to understand the inner workings of the product configuration process and the factors enabling its proper execution. This is remarkable considering the fact that there has been a great deal of research studying possible ways to increase the compatibility between customization and responsiveness. For example, research has theoretically and empirically demonstrated the effectiveness of such principles as product modularity (Forza and Salvador 2002a; Tu et al. 2004), set-up time reduction (Shingo 1985), form postponement (Lee and Tang 1997; Rabinovich and Evers 2003), and product platforms (Tatikonda 1999; Krishnan and Gupta 2001), among the others.

Most of the research on product configuration published to date caters to the Information Systems literature which, for its very mission, is centered on the development of the tool – the product configurator – rather than on understanding how the information generated by this kind of tools supports business performance. For example, Information System research has been investigating what approaches can be followed to ease the codification of product knowledge in the development of a
product configurator (McGuinnes and Wright 1998) or what solutions can be implemented to improve speed and accuracy of on-line product configurators (Slater 1999).

To address this gap in the literature, we propose a theoretical model that relates the availability of information supporting the product configuration task to the responsiveness of a company – defined as the speed and reliability of the company in serving its customers. We test this model on a sample of 108 Italian plants operating in the machinery industry. We develop new measures for the constructs subsumed in our theory and we then test the hypotheses derived from the theoretical model. We then discuss the findings, highlighting the limitations of the study and its implications for practice and future research.

2. An Information Processing View of the Product Configuration Task

From an organization design perspective, the more a company customizes its products to its clients’ needs, the higher is the uncertainty associated with the task of selling and delivering these products. The front-end of the organization, for example, may have a difficult time estimating the feasibility of a specific customer’s request. Likewise, the back-office may experience serious difficulties envisaging technical solutions to comply with this request. Customization, in other words, leads to task uncertainty.

Galbraith (1977) proposes that task uncertainty can be thought of as “the difference between the amount of information required to perform the task and the amount of information already possessed by the organization” (p.37). Hence, the decision of a company to offer customized products leads, ceteris paribus, to an information processing gap, i.e. the organization does not have all the information it needs to perform its task at the desired performance level, be it time, cost, or any other measure of performance. In the case of customization, the nature of the information processing gap can be thought of in terms of, for example, the lack of information regarding the possibility and profitability of complying with a given customer request.
Traditionally, companies offering customized products have addressed such information processing gaps by using organization design principles, which either reduce the needed information processing capacity or increase the available information processing capacity (see Galbraith 1977). Typically, the information processing capacity is increased by establishing lateral relations. This means that customization-related problems are solved by cutting across functional boundaries, such that all the individuals and units possessing information relevant to address a customer problem work jointly towards a feasible solution. In practice, this means that often front-end and back-end of the company work together in order to sell and deliver customized solutions (Forza and Salvador, 2002b).

On the other hand, companies have tried to reduce the information processing requirement needed to sell and deliver customized products. The simplest and easiest way to do this is to rely on slack resources, i.e. to simply reduce the level of performance. For example, an organization facing serious information processing constraints in the tendering process may allow itself more time to come back to the customer with a quotation. Alternatively, organizations may create self-contained tasks, meaning that they can reduce the degree of division of labor and place the different actors in charge of the sale and delivery of customized products under the same organizational unit. This is done, for instance, by having salesmen with strong technical background deal with customization, without the need to involve the technical office.

More recently, companies have begun to design configurable product families to reduce the information processing requirements induced by customization, de facto engaging in the organization design strategy known as environmental management. This is because, for a configurable product family, product variants are generated by combining sets of predefined components, i.e. no new components are designed to address the customers’ needs. Stated otherwise, addressing the market by means of a configurable product family means constraining the product offer of a company within a

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1 A predefined component, in turn, is either a standard component (e.g. one notebook’s USB plug), a standard component with variants (e.g. the notebook hard drive, offered in 80, 100, 120GB capacities) or a parametric component (i.e. the sleeve for a custom suit, continuously adjusted to fit the customer arm’s length) (Mailharro, 1998; Tiihonen et al, 1995).
pre-determined product space (Lancaster 1970; Tseng and Piller 2003). Evidently, relying on a pre-determined product space means drastically cutting uncertainty concerning the sale and delivery of customized products.

By serving the market through a configurable product family, a company does not have to custom-design its product variants. The design task in order acquisition is in this case substituted by a different task – the product configuration task. Mittal and Frayman (1989) define this task as one for which: (1) no new components are designed during the configuration task; (2) components are connected to other components under a set of pre-defined compatibility constraints; and (3) solutions (configurations) specify not only the components in the configuration but also how they are related.

Companies that serve heterogeneous customers’ needs through configurable product families can naturally take advantage of an additional organization design strategy to increase their information processing capability, by establishing formal information systems. Such systems would help closing the information processing gap by providing problem-solving information to the appropriate organizational entities. In practice, these systems take the form of product selection and configuration assistants (product catalogues, e-catalogues, product configurators and users toolkits, etc.)

While the potential of these systems for closing the information processing gap in the product configuration task may appear obvious, we argue it is not. In the next section we elaborate on this point finding conditions under which the information used to support the product configuration task could be more or less effective in reducing the trade-off between customization and responsiveness.

3. Model formalization

3.1 Information Supporting the Product Configuration Task
The existence of a trade-off between customization and responsiveness automatically sets responsiveness as a potential order-winning criterion among companies that offer customized products (McCutcheon et al., 1994). A high responsiveness to the customers implies that customers have to
“sacrifice” less in order to get a tailored product, and thus they would be more willing to make a purchasing decision (Pine and Gilmore, 2000). Importantly, responsiveness of a company to its customers is not only a matter of order fulfillment. Indeed, especially when customized products are offered, a substantial chunk of the time to serve a customer is the tendering lead time, defined as the time span from the first customer contact to order entry (Hvam et al., 2006).

The more a company is willing to tailor its product offer to its customers’ needs, the more it is like to experience an information processing gap in the execution of the product configuration task. On the one hand, this is due to the fact that more information has to be collected from the customers, process that is also referred to as elicitation (Zipkin, 2001). On the other hand, the company has to feed back more information to customers, providing them with articulated answers to their complex and variegated needs.

The information processing gap gets manifest in the context of the product configuration process as the lack of promptly available information to answer to the customer’s requirements, doubts, etc. Under this circumstance, the front-end of the organization has to engage in a search for the missing information across the organization, typically connecting to the back-end, in which most product expertise lies. The immediate consequence of this information retrieval activity is an increase of the total time needed to revert back to the customer with a feasible proposal – typically a bid (Forza and Salvador, 2002). The tendering lead time, in other words, is negatively affected.

An information processing gap in the product configuration process has also potentially serious negative consequences on the reliability and speed of order fulfillment. This further liability originates because information retrieval processes imply multiple information exchanges (Forza and Salvador, 2002b). Since every information exchange creates the risk for misinterpretation and corruption of information (Shannon, 1948), the ultimate output of the product configuration process is likely to be affected by errors. These errors would tend to make the reliability of promised delivery dates erratic. In
addition, because of the need to fix configuration errors during the order fulfillment process, delivery lead times would tend to get longer as well.

Since the information processing gap in executing the product configuration task is, by definition, reduced through the provision of readily available information supporting the product configuration task, we can conclude the following:

**Proposition 1:** The prompt availability of information supporting the product configuration task is positively associated to the responsiveness in serving the customer.

### 3.2 Learning from Past Product Configurations

Full availability of information supporting the product configuration task, however, offers no guarantee for a flawless and swift product configuration process. The information that the sales staff has at their disposal might be i) affected by errors, or ii) presented in an unduly complex or unfamiliar format and therefore difficult to use or interpret (Dellaert and Stremesh, 2005). In the first case, although the organization may be able to rapidly produce a quotation, errors would become evident in order fulfillment, thus increasing the delivery time and compromising delivery reliability. Likewise, in the second case, the sales staff, confused by the information meant to support the product configuration task, might find it difficult or even impossible to swiftly provide the appropriate answers to requests of customers or to make the right questions. Also in this case, errors and ultimately delays will likely follow.

The risk that the information supporting the product configuration task presents errors or is of difficult use is very real. Reasons for this are numerous and include factors such as the differences between the way product specifications are expressed by customers and the way they are listed in the product information prepared by the technical staff in the back-office. Other reasons are misinterpretation of technical specifications on the part of the sales staff as well as the presence errors in the codification of technical product information (Salvador and Forza 2004).
The quality of information supporting the product configuration task is ultimately determined by the product development process for the configurable product family. The product development process, in fact, is not confined to only defining the features of the product family, the technical solutions needed to deliver these features and the characteristics of the manufacturing process needed to build the product family. It also documents the output of the product design activity by releasing a series of documents (i.e., technical catalogues) and tools (i.e., spreadsheets, product configurators, etc.) aimed at supporting the product configuration task (Clement et al. 1995). In other words, it is the product development process which releases the information supporting the execution of the product configuration task.

A clear input to the product development process is essential to ensure the quality of the information supporting the product configuration task. Specifically, the company has to have clear ideas concerning what customer needs are going to be targeted with the product family and of what technical solutions will be used to implement such features (Simpson et al. 2007). Fundamental to acquiring this knowledge is the analysis of past product configurations, much like historical time series sales analysis is fundamental for a good sales forecasting process.

The organization, in other words, has to be able to learn from past product configurations in order to maximally support the execution of the product configuration task. For example, it may be that a set of product features tend to co-vary, meaning that they subsume a latent need of the customer that has to be understood and exploited. This knowledge should ultimately be incorporated in the information supporting the product configuration task, so that salespeople would be aware of this latent need of a group of customers and could address it appropriately (Forza and Salvador, 2007). Likewise, the organization has to understand how its technical knowledge and manufacturing resources are being used to support these needs. For example, it has to recognize that the aforementioned latent need is associated with a set of apparently unrelated product components. This knowledge, in turn, would increase the reliability of the product configuration task by making it easier to automatically associate a
customer-specified feature (e.g., a set of interrelated customer’s needs) with a product structure (e.g., a chunk of a bill of materials) or a process structure (e.g., a production sub-sequence).

We can then propose the following:

**Proposition two:** The effect of the availability of information supporting the product configuration task on the responsiveness in serving the customer is moderated by the organization’s capacity to learn from past product configurations.

A graphical representation of the model subsumed by the two propositions is provided by Figure 1.

### 4. Method

#### 4.1 Survey design and execution

**4.1.1 Population, Sampling and Resulting Sample**

Our target population is comprised of Italian manufacturing firms offering assembled configurable technical products. To identify the target population, a selection of 39 four-digit SIC codes were screened based on the judgment of experts – mostly business consultants and product configuration experts. The resulting sampling frame, included the following SIC codes: 2511, 2522, 2531, 3431, 3432, 3433, 3441, 3444, 3499, 3523, 3531, 3533, 3536, 3541, 3542, 3544, 3545, 3549, 3551, 3552, 3553, 3554, 3559, 3563, 3568, 3569, 3581, 3585, 3589, 3599, 3612, 3621, 3636, 3643, 3648, 3699, 3713, 3714, 3743. These firms predominantly operate in the machinery industry, industry which sees Italy as one of the top five exporting nations globally.
A special effort was made in composing the sampling frame to assure a balanced representation of firms across different sizes. Given the fact that the distribution of the firm sizes in Italy is highly skewed toward the very small sizes, stratified disproportionate random sample approach was adopted. Hence, the firms of the initial target population were first grouped into three strata; very small (<30 employees), medium-small (30-99 employees), and medium and large firms (≥100 employees). Subsequently, a similar number from each stratum was randomly selected to be included in the sampling frame.

Questionnaires were mailed to 1150 firms. The resulting sample comprised 122 firms; a response rate of 10.6%. Among these firms, 31% were very small; 43% small and medium-small; 26% medium and large firms, thus indicating that no self selection took place in terms of company size. Furthermore, 154 randomly selected non-responding firms (16.3% of the designed sample) were contacted by phone to investigate potential non-respondent bias. No substantial bias was detected.

In the course of the analysis an additional four firms were deleted due to the missing data on the specific variables used in the study. Another 10 firms, were subsequently removed as they were not manufacturing assembled products, thus falling outside the target population. Therefore, the sampled used in this study totals 108 firms.

4.1.2 Respondents

Questionnaires were targeted to single respondents, more specifically to plant superintendents or general directors who could, within reason be expected to have an overall picture of the entire firm. This comprehensive understanding of the firm’s entire operations was considered important since the product configuration task does not only include the activities performed in the technical offices, but impact also those performed in other departments such as sales and marketing (Forza and Salvador 2002a). Furthermore, since the survey was submitted to a population consisting primarily of smaller and medium enterprises, it would not be unusual to come across lower level managers who might not have the knowledge, overview and skills to provide reliable answers. Plant superintendents or general
directors, on the other hand, would be able to retrieve the required information from his or her subordinates if needed.

4.1.3. Questionnaire Design, Pre-Test and Administration

A questionnaire was designed that comprised of straightforward, unambiguous, and easy to understand questions. Since the topic of product configuration lends itself for the use of complex terminology (Soininen et al. 1998), and this terminology varies across companies (Forza and Salvador 2002a) we worded our questions to ease a uniform and correct interpretation. The survey instrument was then pre-tested in four firms representing the different industrial environments that were included in the population. As a result, changes were made to approximately 20% of the questions.

To enhance the response rate, respondents were promised a personalized report in which their firm would be benchmarked to the overall sample of respondents as well as to similar firms in the respondent pool.

All questionnaires have been systematically controlled for missing values etc., upon their return in an effort to ensure data quality and completeness. Additionally, a set of automatic controls was performed on the data which highlighted inconsistencies between interrelated answers and providing an indication of what information had to be asked again to respondents.

4.2. Measure Development and Validation

Given the novelty of the constructs involved in this study, we had to develop new measures both for the dependent and independent variables. With the exception of the control variable “Degree of Customization” we developed multiple-items measures and we anchored their items on 5-point Likert scales, for which respondents could either (1) completely disagree, (2) disagree, (3) neither agree nor disagree, (4) agree, and (5) completely agree. The reliability of these measures in the form of internal consistency was tested using the Cronbach’s alpha coefficient (Cronbach, 1951; Nunally, 1978; Hull
and Nie, 1981), while construct validity in the form of construct univocity have been checked through principal component analysis (see Table 1).

| INSERT TABLE 1 HERE |

The **Responsiveness in serving the customer (RESPONSE)** refers to the capacity of firms to rapidly and reliably respond to its customers’ needs, both during order acquisition and during order fulfillment activities. RESPONSE was operationalized by asking the respondents to state whether the performance of their firm was better than that of their competitors across the following parameters: (a) tendering lead time, (b) order fulfillment lead time and (c) order fulfillment punctuality.

The **Information Supporting the Product Configuration Task (IPC)** refers to the provision of readily available information supporting the product configuration task both for sales and after-sales. IPC was operationalized by asking respondents whether the sales staff has prompt access to information on product technical feasibility or whether it experiences lack of information regarding (a) the product configuration alternatives (realized or realizable), (b) the cost of each alternative as well as (c) the delivery time of the chosen alternative. The operationalization IPC included one additional item which asked the respondents about the product information gap the after-sales personnel is experiencing in after sales activities where the product configuration task is repeated, at least partially.

The organization’s **Capacity to Learn from Past Product Configurations (LPC)** refers to the availability of information on past product configurations that can support the (re)definition of (1) the product space the firm decides to by asking the respondents whether the information on the past product configurations was easily used for (a) market analysis as well as (b) for production planning and improvement. This variable had a Cronbach alpha of 0.628 which, although lower than the generally accepted rule of thumb of 0.700, is still acceptable for a new scale (Nunally, 1978). The somewhat lower alpha can furthermore be attributed to there being only two items in the measure.
The Degree of Customization (CUSTOM) refers to how customized are the products offered by the company. This measure is an index operationalized by asking the respondent to rate what percentage the products made by their firm fell in each of the following categories: (1) products made based on customer specifications; (2) products partially made based on customer specifications; (3) standard products with options; (4) basically standardized products; (5) highly standardized products. These five answers have been linearly combined weighting them respectively with the following coefficients: 5, 4, 3, 2 and 1. The result has been divided by 100, thus obtaining a score ranging from one (no customization) to five (highly customization).

5. Data analysis and Discussion

Based on Aiken et al. (1991), we test our hypothesis by means of a linear regression model wherein the moderation effect is captured by a mixed second order term. We also control for the degree of product customization, this estimating the following model:

\[
\text{RESPONSE} = b_0 + b_1 \times \text{IPC} + b_2 \times \text{LPC} + b_3 \times \text{LPC} \times \text{IPC} + b_4 \times \text{CUSTOM} + \varepsilon
\]

The descriptive statistics and correlations for the study variables IPC, LPC, CUSTOM and RESPONSE are presented in Table 2.

5.1 Regression Diagnostics

Common-Method Bias. Common methods variance is defined as the overlap in variance between two variables attributable to the type of measurement instrument used rather than due to a
relationship between the underlying constructs (Avolio et al 1991). Since we used a single respondent measurement procedure we opted for checking for common-method bias. To test for common method bias we used the Harman’s single-factor test (Andersson & Bateman 1997, Aulakh & Gencturk 2000) After loading all the variables (which variables LPC, IPC, CUSTOM) into a factor analysis, the unrotated solution shows 2 significant factors, none of which accounts for the majority of the covariance among the measures.

Regression Assumptions, Normality and Multicollinearity. The distribution of the residuals is approximately normal with a mean of zero and a standard deviation of 0.99. The plot of standardized residuals against standardized predicted values of the dependent variable shows a horizontal band of residuals with no discernable patterns. This suggests that the relationship between the dependent and the independent variables is linear. The spread of the residuals does not change over the range of independent variables which means the equality of variance assumption is not violated. The Kolmogorov-Smirnov normality check of the model’s standardized residuals provided a significance value of 0.200, well above the minimum of 0.05 which indicates normality of the model. The significant correlation between the independent variables IPC, LPC and CUSTOM (see Table 2) could make unreliable the estimated regression coefficients. The variance inflation factor (VIF) was 18.745, which indicates that multicollinearity can seriously bias parameter estimates (Cohen et al., 2002). Following Aiken et al. (1991) we run the regression analysis after centering each variable so that its mean is zero. Collinearity diagnostics were satisfactory after this rescaling of the variables.

5.2 Test of the Proposed Model

The results of the regression analysis are reported in Table 3. The regression model is statistically significant, with an R² of 15%.

| INSERT TABLE 3 HERE |
Hypothesis 1, which concerns the positive association between Information supporting product configuration (IPC) and firms’ responsiveness in serving the customer (RESPONSE), is represented by the term $b_1 \times IPC$ in the regression analysis. This term results to be statistically not significant ($p=0.423$). Therefore, the hypothesis that smaller information gap in the product configurations task lead to quicker and more punctual response to customers is not supported.

Hypothesis 2, which postulates the moderating effect of the firm’s capacity to learn from past product configurations (LPC) on the relationship between the information for product configuration (IPC) and firm’s responsiveness in serving the customer (RESPONSE), is represented in the regression model by the interaction term $b_3 \times LPC \times IPC$. This term is statistically significant at 5% level ($p=0.016$) as expected.

The nature of the moderation effect was analyzed in more detail to get a better understanding of the way in which the moderator changes the effect of the independent variable on the dependent variable. For this the data set was split into two sub-sets, by taking a median split on LPC, the moderating variable. Following Jaccard and Turrisi (2003) the regressions were subsequently plotted (see Figure 2). The moderation effect is confirmed since the resulting regression lines do not run parallel. Contrary to the expectations however, the lines did not have the same direction yet different slopes but had opposing directions all together. Interestingly, however, the model is not supported in the same way in the two sub-samples (see Table 2). The model holds also in the low LPC sub-sample with 7.6% of the dependent variable variance is explained by the independent variables. However, the coefficient related to IPC is not significant, meaning that DV variance is explained by the variable CUSTOM. On the contrary, the model is strongly significant in the high LPC subset, where 26.8% of the dependent variable variance is explained by the independent variables, with the coefficient of CUSTOM not statistically significant. Therefore, it can be concluded that LPC acts as a suppressor of the relation between IPC and RESPONSE.
6. Discussion, Limitations and Conclusions

The prompt availability of information to support the product configuration task is considered as a fundamental principle to reduce the trade-off between customization and responsiveness. We find that provision of this information does not necessarily improve the level of performance of the product configuration task. This performance, instead, appears to heavily depend on the capacity of the organization to learn from past product configurations. By means of such learning process companies can better decide what to offer in the future, how to offer it and how to deliver it. Ultimately, our findings suggest that only if this learning process is operating within the company, then investment in knowledge codification would make sense to support the product configuration task.

The novel research question we address forced us to conceptualize new constructs and to develop measures for these constructs (e.g., Information Supporting the Product Configuration Task, Capacity to Learn from Past Product Configurations and Responsiveness in Serving Customers). Although, as any newly developed scale, these measures are improvable, we believe these constructs and measures may be usefully incorporated in subsequent research projects either directly or tangentially dealing with product configuration. Replication studies would also be welcome, as our research is only meant to offer a preliminary assessment of the relation between the factors affecting the effectiveness of the product configuration task in general, and the role of learning in the upstream product family development process.

Research dealing with the product configuration task and the associated learning processes, in our opinion and experience, is also extremely important for practice. A fundamental reason for this is that most kinds of tangible and intangible products are configurable. Contrary to a diffused belief, in fact, to be configurable a product family does not necessarily have to be modular – a far more demanding requirement (Forza and Salvador 2007). Also, the very notion of product configuration
does not have to be taken too narrowly. A vacation package can be thought of as a configuration of different services, as well as a credit card contract or a customer’s basket in Amazon.com. All these business face a similar challenge: learning from past customer transactions in order to timely offer the “right” configuration of their services to ever demanding and differentiated customers. This is not only a marketing issue, nor an IS, issue; operational processes, in fact, have to be devised, implemented, controlled and improved in order to link the customer, front-end and back end of the company for fast and efficient customization.
Figure 1: The Theoretical Model
Capacity to learn from past product configurations $> 3$ (median)
Capacity to learn from past product configurations $= 3$ (median)
(effect of IPC not significant)

Figure 2: The Moderating effect of LPC
<table>
<thead>
<tr>
<th>Variable name</th>
<th># items</th>
<th>Cronbach’s Alpha</th>
<th>First Eigenvalue</th>
<th>% variance explained</th>
</tr>
</thead>
<tbody>
<tr>
<td>Responsiveness in serving the customer (RESPONSE)</td>
<td>3</td>
<td>0.756</td>
<td>2.041</td>
<td>68.03%</td>
</tr>
<tr>
<td>Information supporting the product configuration task (IPC)</td>
<td>5</td>
<td>0.694</td>
<td>2.410</td>
<td>48.19%</td>
</tr>
<tr>
<td>Capacity to learn from past product configurations (LPC)</td>
<td>2</td>
<td>0.619</td>
<td>1.448</td>
<td>72.41%</td>
</tr>
</tbody>
</table>

Table 1: Measures Reliability and Validity

<table>
<thead>
<tr>
<th>Variables</th>
<th>Means (s.d.)</th>
<th>RESPONSE</th>
<th>IPC</th>
<th>LPC</th>
<th>CUSTOM</th>
</tr>
</thead>
<tbody>
<tr>
<td>RESP</td>
<td>3.387 (0.861)</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>IPC</td>
<td>3.355 (0.877)</td>
<td>0.133</td>
<td>1</td>
<td></td>
<td></td>
</tr>
<tr>
<td>LPC</td>
<td>2.830 (1.134)</td>
<td>0.154</td>
<td>0.341**</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td>CUSTOM</td>
<td>2.692 (0.967)</td>
<td>0.297**</td>
<td>0.216*</td>
<td>0.175</td>
<td>1</td>
</tr>
</tbody>
</table>

* Correlation is significant at the 0.05 level (2-tailed)
** Correlation is significant at the 0.01 level (2-tailed)

Table 2: Descriptive statistics and correlation among variables
<table>
<thead>
<tr>
<th>Variable</th>
<th>RESPONSE</th>
<th>RESPONSE</th>
<th>RESPONSE</th>
</tr>
</thead>
<tbody>
<tr>
<td>Full sample</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>IPC</td>
<td>0.17</td>
<td>3.13**</td>
<td>-0.137</td>
</tr>
<tr>
<td>LPC</td>
<td>0.059 n/a</td>
<td>n/a</td>
<td>n/a</td>
</tr>
<tr>
<td>Interaction (LPC*IPC)</td>
<td>0.172**</td>
<td>n/a</td>
<td>n/a</td>
</tr>
<tr>
<td>CUSTOM</td>
<td>-0.210</td>
<td>-0.170</td>
<td>-0.262**</td>
</tr>
<tr>
<td>Sub-sample</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>LPC &gt; Median (3)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>IPC</td>
<td></td>
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<tr>
<td>LPC</td>
<td></td>
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<tr>
<td>Interaction (LPC*IPC)</td>
<td></td>
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</tr>
<tr>
<td>CUSTOM</td>
<td></td>
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<tr>
<td>LPC ≤ Median (3)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>IPC</td>
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<tr>
<td>LPC</td>
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<td>Interaction (LPC*IPC)</td>
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<tr>
<td>CUSTOM</td>
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</tbody>
</table>

R² 0.15
F 4.546 *** 6.042 *** 2.828 *
df 4,108 2,36 2,72

* p < .10
** p < .05
*** p < .01

Table 3: Results of regression analyses
References


