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How do managers actually choose suppliers? Evidence from revealed preference data

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Abstract: Supplier selection plays a pivotal role in the success of any organization as it significantly reduces purchasing costs and increases corporate competitiveness. At the same time, it is a very challenging task as decision-makers have to tradeoff among different supplier attributes. In this paper, a discrete choice model of supplier selection is developed, based on revealed preference data collected from an electrical equipment manufacturer in Poland. We explore the importance of different attributes for the initial choice and subsequent switching of suppliers. The proposed logit model is proceeded by a nonparametric analysis conducted through the Chi-square Automatic Interaction Detector (CHAID) framework, which serves exploratory purposes. We find that delivery and reliability play a crucial role in decision-making with regards to choosing suppliers and switching them if necessary.

Keywords: supplier selection, purchasing, supply chain management, revealed preferences, discrete choice analysis, logit model, CHAID prediction model

JEL codes: C01, C44, D22

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1 Introduction

How do buyers evaluate and select suppliers? Which factors play a significant role and create competitive advantage? When do buyers switch from selected suppliers and hire new trading partners? How can challenger firms outperform incumbent suppliers? These questions are crucial from both demand- and supply-side perspectives and affect the success of strategic management of any enterprise. The importance of selecting the most competent suppliers has increased recently as companies rely heavily on outsourcing a significant part of their activities. Furthermore, supplier selection has become a relatively dynamic phenomenon, as buyers often decide to move away from the existing supplier relationships and consider alternative vendors.

As relying on external vendors becomes more important in many industries, so does the supplier selection process (Kannan and Tan, 2002; Yan et al., 2003; Li et al., 2006). Furthermore, with the rapid proliferation of information technologies in supply chain, the importance of supplier management has been amplified during recent decades (Kaplan and Sawney, 2000; Hall and Braithwaite, 2001). Several empirical studies also support the fact that purchasing firms indeed consider the role of suppliers to be crucial for business performance of the buying firm (Choi and Hartley, 1996; Gonzalez, et al., 2004).

While the supplier selection literature is rich in terms of conceptual models, decision support systems, and simulation studies, market utility-based approaches such as discrete choice analysis have received relatively little attention. Nevertheless, several authors have attempted to apply these methods to assess how decision-makers make choices when dealing with different supplier profiles. These methods are based on assessing the relative weights of various attributes in managerial decision-making processes. Perhaps one of the earliest and most prominent studies in this field is the discrete choice analysis performed by Verma and Pullman (1998). These authors found that purchasing managers' stated preferences regarding the importance of supplier selection criteria do not necessarily coincide with their actual choices. These results indicate that although managers say that quality is the most important attribute for a supplier choice, they actually choose suppliers based largely on cost and delivery performance. Van der Rhee et al. (2009) explored how executives and managers trade-off amongst various competitive dimensions, such as cost, delivery performance, flexibility, and value-added service/support when selecting a supplier for raw materials, with the condition that minimum acceptable quality is guaranteed. They tested the suggested model for several European countries.

All the above-mentioned studies have applied stated preference methods to analyze decision-makers' preferences during the supplier selection process. The stated preference discrete choice technique relies on respondents making choices over hypothetical scenarios (Carlsson, et. al., 2010). Respondents are asked to choose the 'best' alternative from among a set of hypothetical scenarios, which are completely described by a set of attributes generated from an experimental design (Hicks, 2002). Stated preference methods typically utilize a statistical design that eliminates collinearity among the attributes. Conversely, revealed preference techniques use observations on actual choices made by people to measure preferences. The primary advantage of the revealed preference technique is the reliance on actual choices, avoiding the potential problems associated with hypothetical responses such as strategic responses or a failure to properly consider behavioral constraints. While the stated preference approaches in the supplier selection literature have shown certain consistency and robustness, there is a need for designing a discrete choice model and testing it on actual market data.

Li et al. (2006) was perhaps the first study to extend the use of DCA in the supplier selection literature by comparing the attributes of an existing supplier to that of a new supplier. The fundamental difference between this approach and the traditional DCA was that the respondents were asked to indicate the profiles of their current suppliers, and the experimental alternatives were designed based on those. In other words, each respondent received a hypothetical alternative supplier profile tailored to their particular situation. These authors also extended the theoretical framework to include supplier switching inertia. They confirmed the existence of switching inertia and, as a result, the competitive asymmetry between current and new suppliers from a demand-side perspective. This combination of stated and revealed preferred approaches prepared the ground for conducting a complete revealed preferred analysis, solely based on actual market performance.

Our study, based on supplier-performance data collected from an electrical equipment manufacturer in Poland, proposes a discrete choice model aimed at understanding how decision-makers actually select suppliers and when they switch to new alternatives. A two-staged analysis is proposed consisting of nonparametric and parametric models. The first part is conducted through the Chi-square Automatic Interaction Detector (CHAID) analysis and is mainly used for exploratory purposes. CHAID has gained popularity as a classification tool in various disciplines, including consumer marketing (e.g., Baron and Phillips 1994; Riquier, Luxton, and Sharp 1997), direct marketing (e.g., Elsner, Krafft, and Huchzermeier 2003;

Schellinck and Groves 2002), geography (e.g., Casas 2003), education (e.g., Grobler, Bisschoff, and Moloi 2002), and gambling (e.g., Welte, Barnes, Wieczorek, and Tidwell 2004). To the best of the author's knowledge this is the first attempt of applying CHAID to supplier selection decision-making. CHAID diagnosis is followed by a logit model (Hosmer et al., 2013) aimed at analyzing the relative importance of different supplier attributes on selection or switching decisions. The main attributes include cost, quality, attitude and professionalism, reliability, and delivery (expressed as a combination of compliance with due date and flexibility for changes in demand). Company size and supplier category are used as control variables when necessary. All the explanatory variables are discussed in detail in the Methods section.

The rest of the manuscript is structured as follows: first, we describe the research methods and data analysis procedure applied in this study. Section 3 summarizes the results of the empirical analysis. A discussion of the main implications is offered in Section 4 , followed by Section 5 which concludes and provides directions for future research.

2 Methods

While most of the previous supplier choice studies (e.g., Verma and Pullman, 1998; Li et al., 2006; Van der Rhee et al., 2009; Watt et. al., 2010) were based on stated preference surveys, we use real market data to analyze how managers actually choose and switch suppliers. Despite our data is observational rather than experimental, the desirable property of linear independence of attributes holds: variance inflation factors (VIFs) for all the attributes do not exceed 1.3, which is lower than the commonly used thresholds for detecting multicollinearity (e.g., 5 or 10) (Mansfield and Helms, 1982). In the following section, we present the data structure and relevant variables used in our study. This is followed by an overview of the econometric framework.

2.1 Data and variables

Supplier-performance data was collected from an electrical equipment manufacturer in Poland, based on their procurement records of the last ten years and further field research. Several visits were conducted to the company in order to meet the responsible managers and business unit representatives. They were interviewed for collecting additional information on selected, rejected or switched suppliers and necessary documents were obtained to have detailed understanding of the gathered data. Finally, the collected data was rearranged and brought to a suitable form for a discrete choice analysis. The final dataset contains 1,253 suppliers considered by 57 decision-makers working in the same firm. The company has classified the project teams into eight departments based on commodity groups they deal with. Each decision-maker represents either an individual or a project team, led by a project manager. Switching data was only available for constant suppliers (explained in the following) and consisted of 330 different providers.

The output (dependent) variables were supplier choice and supplier switching, which are both binary variables labeled as 1 and 0, depending on the outcome. Key supplier attributes (independent variables) included cost, quality, attitude and professionalism, reliability, and delivery. All the independent variables were described by three levels – low, average, and high – where average normally corresponded to market standards. Supplier category (one-off, infrequent, frequent, constant, and compulsory) and company size (micro, small, midsize, and large) were used as control variables whenever they were significant. The former was described by five levels – one-off, infrequent, frequent, constant, and compulsory – based on frequency of payment contracts and types of collaboration. The latter had four levels – micro, small, midsize, and large – based on the number of employees. While most of the original data was numerical, all the variables were expressed in categorical terms due to confidentiality reasons. All the predictor and response variables are described in Table 1 (frequency distributions of all the variables are presented in Table A1 in Appendix A).

2.2 Empirical framework

The analysis was conducted using both parametric and nonparametric methods. Nonparametric methods are often used very successfully in different applied scientific disciplines to identify "most typical" and "most atypical" behavior (von Eye, Spiel, & Wood, 1996). While there are several different types of nonparametric methods, each of them can be applicable depending on specific problem formulation and underlying data structure. CHAID analysis is a technique employed to discover relationships between a categorical response variable and other categorical predictor variables, where a statistically significant result identifies their mutual dependence and the relationship between them. CHAID analysis tries to look for patterns in datasets with multiple categorical variables and builds a model in the form of a decision tree by splitting the sample or the target dependent variable (Kass, 1980). In other words, this algorithm automatically bands predictors into discrete groups so that the resulting discretized variables are associated with the dependent variable as much as possible (according to the significance of the chi-square statistic).

Table 1. *Key variables used in CHAID and logit models*

Variable name	Description	Domain
Supplier chosen	Indicates if a supplier is selected or rejected	*{1, 0}*
Supplier switched	Indicates if an initially chosen supplier is switched or not	*{1, 0}*
Supplier category	Based on contract types and frequencies	*{one-off, infrequent, frequent, constant, compulsory}*
Company size	Based on number of employees	*{micro, small, midsize, and large}*
Cost	Purchase price, as well as additional delivery or maintenance costs	*{low, average, high}*
Quality	Level of satisfaction with end products based on an internal rating system	*{low, average, high}*
Attitude and professionalism	Ease of working with the supplier including communication system	*{low, average, high}*
Reliability	Combined rating based on durability of end products and required regular maintenance level	*{low, average, high}*
Delivery	Combined rating based on compliance with due date and flexibility for changes in demand	*{low, average, high}*

CHAID analysis is ideally positioned for data with large sample size, as the predictor variables are repeatedly split to create categories with equal numbers of observations to get a final outcome (Legohérel, et al., 2015; McCarty and Hastak, 2007). In this study, the sample size of 1,253 suppliers allowed us to effectively apply CHAID. From a managerial perspective, this algorithm automatically searches for important nonlinearities and interactions and helps identify combinations of attributes that are associated with the highest and the lowest probability of being chosen. In this study, we use CHAID as a diagnostic technique to partition the dataset into several segments, which differ by the misclassification error of a logistic regression model. Even though this analysis was mainly used for exploratory purposes as a more actionable alternative to the descriptive analysis, it also proved useful for understanding that the hierarchy of attributes identified by CHAID is consistent with the results of more traditional parametric modeling.

The supplier performance data used for this study does not include information on specific choice sets, i.e. it only indicates whether a specific supplier was selected or not. This data structure makes the multinomial logit model, commonly used in discrete choice experiments, not applicable. Hence, CHAID analysis was followed by a parametric analysis which was conducted using the binary logistic model (Hosmer et al., 2013). The conditional probability of choosing a supplier characterized by a set of characteristics (equation 1) was estimated using the maximum likelihood method:

$$prob(chosen_{sij} = 1|x'_{sij}) = \frac{exp(x'_{sij}\beta_j)}{1+exp(x'_{sij}\beta_j)} \quad (1)$$

where s identifies suppliers, i – decision-makers, j – departments and x'_{sij} is the vector of attributes for supplier s considered by individual i from department j, while β_j is the vector of parameters representing department j's preference towards each attribute. The utility obtained from choosing supplier s depends on the characteristics of the supplier and can be expressed by the following equation:

$$U_{sij} = x'_{sij}\beta_j + \varepsilon_{sij} \quad (2)$$

where the unobserved term ε_{sij} is assumed to have a logistic distribution. Decision-maker i from department j selects supplier s if $U_{sij} > 0$.

The number of observations per individual decision-maker is rather small in many cases, which is why we focus on accounting for the possible heterogeneity of preferences across departments. This heterogeneity was tested by explicitly introducing dummy variables for departments (i.e., fixed effects of departments), as well as their interactions with attribute ratings. This specification allowed each department to have its own set of parameter estimates in the model. The preference towards accounting for heterogeneity of departments using fixed effects (dummy variables) as opposed to random effects is explained by the relatively small number of departments (thus, it is unrealistic to assume that individual effects of departments are normally distributed random variables). In addition, the fixed effects model allows individual effects to be correlated with regressors making it less restrictive compared to the random effects model. Models with constant and varying parameters across departments were compared and conclusions were made using the parameters of the most parsimonious model.

As part of both nonparametric and parametric analyses, we also analyzed the determinants of supplier switching, based on a subsample of 330 constant suppliers that were considered for switching. In particular, we analyzed whether the contract with a supplier s was terminated in favor of a new supplier between six months and five years from the moment when supplier s was selected by decision maker i from department j. The conditional probability of switching can be expressed by the following specification:

$$prob\left(switched_{sij} = 1|x'_{sij}\right) = \frac{exp\left(x'_{sij}\beta_j\right)}{1+exp\left(x'_{sij}\beta_j\right)} \quad (3)$$

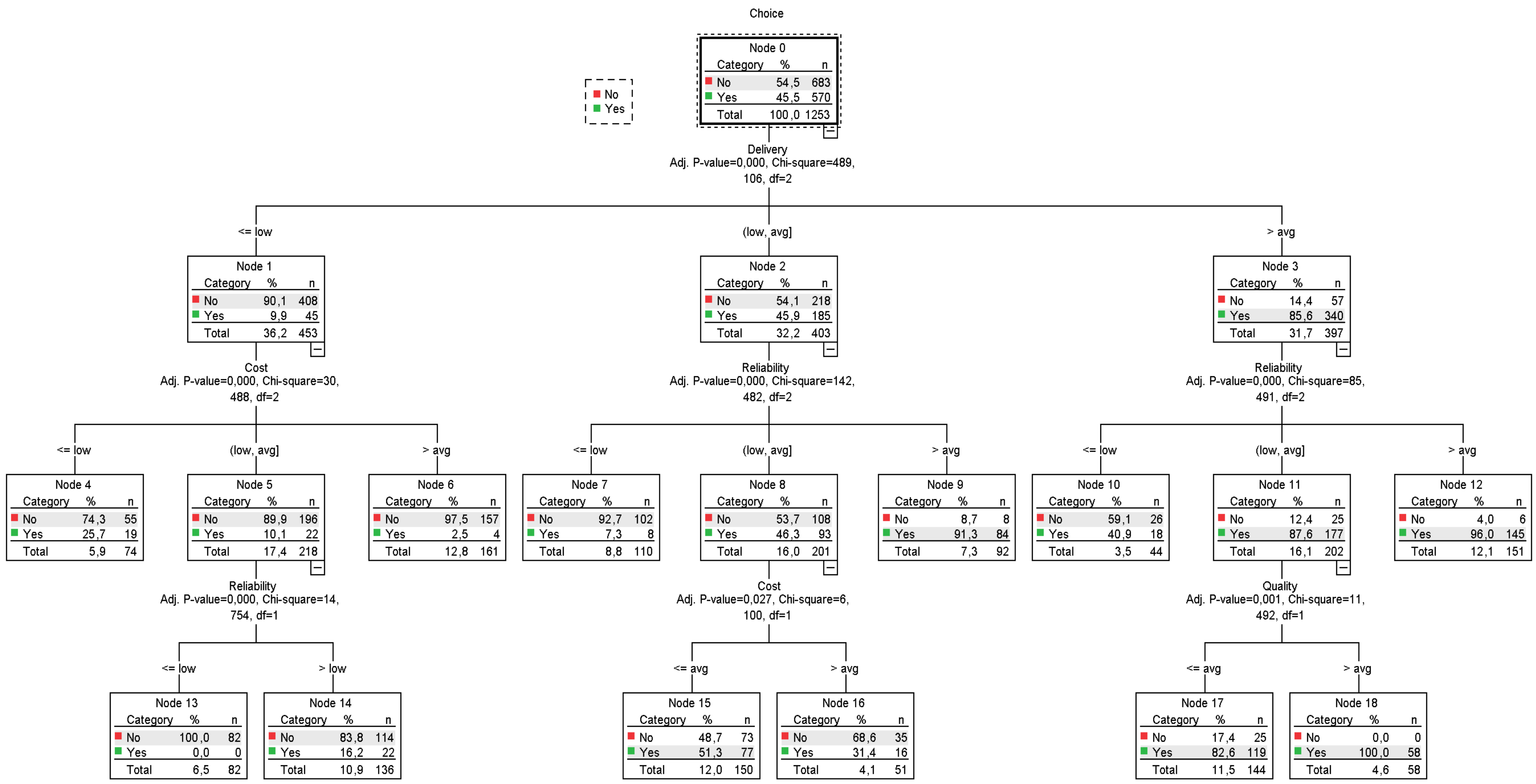
where the right-hand side is identical to that from equation 1.

3 Results

3.1 Initial choice of suppliers

The top node of the CHAID tree built to model supplier choice indicates that the proportion of chosen suppliers in our sample is 45.5% (Figure 1). The probability of being chosen varies the most with the delivery attribute: suppliers with high level of delivery were chosen in 86% of the time, those with average level in 46% of the time, and those with low level in less than 10% of the cases. Reliability was the second most important factor followed by cost. Cost played a significant role when making a selection decision about a supplier with average delivery and reliability. To illustrate, when cost was rated as low or average, the probability of being chosen was 51.3%. For comparison, it was only 31.4% when cost was high and both delivery and reliability were average. Quality was an important determinant of selection probability for suppliers with high delivery and average reliability: having high quality guaranteed that such a supplier was selected, while low or average quality led to selection in 82.6% of cases.

Figure 1. *CHAID tree (dependent variable: supplier choice)*



According to the decision tree (Figure 1), there are three groups of suppliers that were always or almost always selected:

- High delivery, average reliability, high quality (*probability of choice=100.0%, n=58 suppliers*)
- High delivery, high reliability (*probability of choice=96.0%, n=151 suppliers*)
- Average delivery, high reliability (*probability of choice=91.3%, n=92 suppliers*)

Another two groups of suppliers were almost always or almost always rejected:

- Low delivery, average cost, low reliability (*probability of choice=0.0%, n=82 suppliers*)
- Low delivery, high cost (*probability of choice=2.5%, n=161 suppliers*)
- Average delivery, low reliability (*probability of choice=7.3%, n=110 suppliers*)

Supplier category, company size and professionalism/attitude rating were not selected as influential factors by the CHAID algorithm, as the algorithm did not find any splits where these variables would be significantly associated with the probability of supplier selection. The CHAID model correctly classified 84.1% of suppliers, which indicates a high lift compared to a naïve model that would classify all the suppliers as belonging to the most popular category, i.e., “not chosen” (the accuracy of such a model would be 54.5%).

As part of the parametric analysis, we started with a logistic regression model assuming that preferences within the organization do not vary across departments. The model used supplier category, company size, cost, quality, attitude and professionalism, reliability, and delivery as predictors of supplier choice. All explanatory variables were included as sets of dummy variables with their first (“low”) levels used as reference (Model 1 in Table 2). The joint insignificance of two control variables – supplier category and company size – was tested ($\chi^2(7)=0.351$, $p=0.873$). As the p-value of the test exceeded 0.05, at the 5% significance level we excluded the main effects of supplier category and company size from the model, which resulted in a more parsimonious model (Model 2 in Table 2). Even though formally the professionalism and attitude parameter is also insignificant ($p>0.05$), we left the corresponding factor in the model to test whether its insignificance is insensitive to changes in the model specification. That would allow us to account for the possibility that it is important in certain departments, while unsubstantial in others.

Table 2. *Parameter estimates of logit models without heterogeneity across departments (Model 1 and Model 2)*

	Model 1			Model 2		
	Beta estimate	Std. Error	P-value	Beta estimate	Std. Error	P-value
Intercept	0.021	0.052	0.680	0.029	0.035	0.407
supplier_category: infrequent	-0.003	0.041	0.938			
supplier_category: frequent	0.003	0.044	0.938			
supplier_category: constant	-0.026	0.037	0.478			
supplier_category: compulsory	-0.026	0.084	0.761			
company_size: small	0.026	0.032	0.413			
company_size: mid	0.035	0.030	0.246			
company_size: large	0.041	0.034	0.224			
cost: avg	-0.111***	0.024	0.000	-0.109***	0.024	0.000
cost: high	-0.220***	0.028	0.000	-0.220***	0.028	0.000
quality: avg	0.071***	0.024	0.004	0.070***	0.024	0.004
quality: high	0.169***	0.031	0.000	0.170***	0.031	0.000
attitude_professionalism: avg	-0.016	0.023	0.497	-0.014	0.023	0.548
attitude_professionalism: high	-0.035	0.026	0.184	-0.036	0.026	0.172
reliability: avg	0.218***	0.024	0.000	0.222***	0.023	0.000
reliability: high	0.480***	0.030	0.000	0.482***	0.030	0.000
delivery: avg	0.262***	0.024	0.000	0.263***	0.023	0.000
delivery: high	0.552***	0.025	0.000	0.552***	0.025	0.000
AIC	*836.397*			*825.565*		
Log Likelihood	*-399.1985 (df=19)*			*-400.7825 (df=12)*		
Num. obs.	*1253*			*1253*		

**** - significant at the 1% level,*
*** - significant at the 5% level,*
** - significant at the 10% level*

Model 2, which was chosen based on the likelihood ratio test as a more parsimonious model, uses the sets of dummy variables representing the following attributes: cost, quality, attitude and professionalism, reliability, and delivery. Parameter estimates of Model 2 are almost the same as those of Model 1. All the parameters have expected signs: respondents gave preference to higher values of quality, reliability, and delivery and lower values of cost. Keeping in mind that the parameter values of baseline levels (low) were set to zero, according to Model 2 the largest range of parameter estimates (and thus revealed importance) is observed for delivery (0.552) and reliability (0.480). Cost and quality are somewhat less important (their maximum absolute parameter estimates equal 0.220 and 0.169, respectively), while attitude and professionalism is an insignificant factor. Formal pairwise hypothesis testing of equality of parameter estimates shows that high levels of delivery (β_{high}=0.552) are significantly ($p<0.05$) more important than high levels of reliability (β_{high}=0.480), high levels of reliability are more influential than high levels of cost (β_{high}=-0.220), high levels of cost are more important than high levels of quality (β_{high}=0.169), and, finally, high levels of quality are more influential than the high levels of attitude and professionalism (β_{high} and β_{avg} insignificantly differ from zero).

These results are consistent with the hierarchy of factors identified by the CHAID algorithm. Table A2 in Appendix A provides an overview of marginal effects, i.e. changes in predicted probability of selection (based on Model 2) as a result of transitioning from the low to the high level of each attribute (except for the statistically insignificant "attitude and professionalism") holding other attributes constant.

In Models 1 and 2 each factor variable was represented by two parameters associated with the corresponding dummy variables representing average and high levels of each attribute (with "low" used as the baseline), which substantially increased the number of estimated parameters. In order to avoid losing too many degrees of freedom, we transformed ordinal variables into numeric ratings (low - 1, average - 2, high - 3). This transformation assumes equal effects of transitions from low to average and from average to high. According to our logit model with homogeneous preferences (Model 2 in Table 2), this is a realistic assumption, as the difference between coefficients at "high" and "average" is always very close to the difference between coefficients at "average" and "low" (the non-rejection of this equality has also been checked using appropriate likelihood-ratio tests).

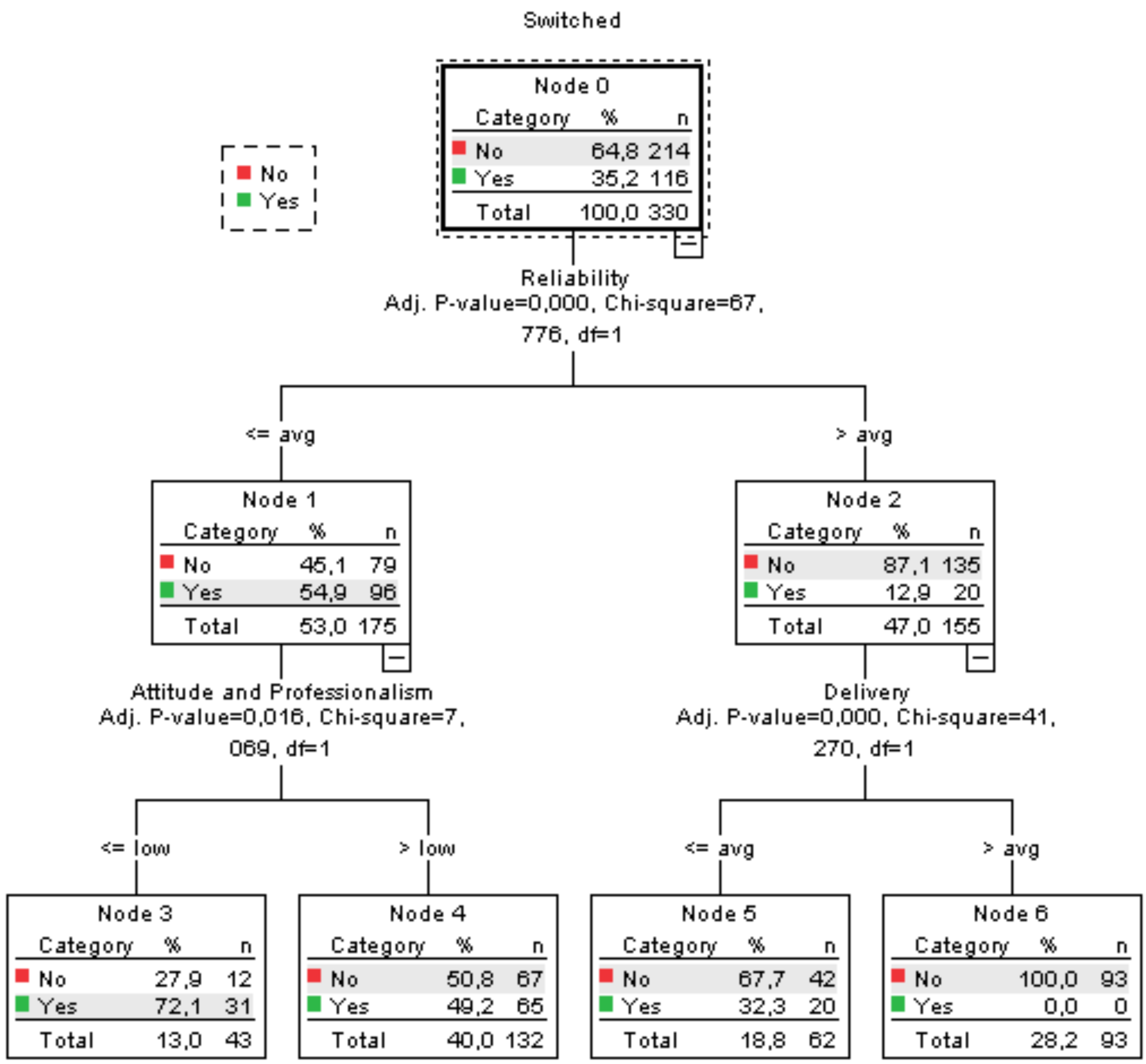
After transforming attributes to numeric ratings (*cost_num*, *quality_num*, *attitude_prof_num*,, *reliability_num*, and *delivery_num*), we estimated the logit model with fixed main effects of departments and attributes, as well as department-ratings interactions thus allowing the importance of attributes to vary by department (Model 3 in Table A3 of Appendix A). The interpretation of main and interaction effects involving "departments" is relative to department 7 (the largest department in terms of number of decision-makers). Model 3 has pointed out very few significant differences among departments (most of them significant at the 10% level, but not at the 5% level). However, a series of joint likelihood-ratio tests were conducted that tested each group of parameters related to departments (6 groups of 7 parameters each). Each group of interaction effects turned out to be insignificant (p>0.1). Moreover, all the main effects and interactions (a total of 42 parameters) related to departments also turned out to be jointly insignificant ($\chi^2(86)=43.729,\ p=0.398$). Thus, no significant differences were found between departments in terms of the importance of attributes involved in the supplier selection process. This conclusion allows us to employ the more parsimonious model defined earlier (Model 2 in Table 2).

3.2 Supplier switching

Similar to the supplier choice analysis discussed earlier, the top node of the CHAID tree for supplier switching indicates that amongst 330 constant suppliers 35.2% were switched within five years after the start of the contract (Figure 2). As supplier switching is time-dependent in nature, we had to take into account the initial contract duration before a switching decision was considered. In other words, a recently chosen supplier would normally have a lower chance of being switched compared to a supplier selected several years ago. For this purpose, we only included suppliers which had contracts of at least six months before they were considered for switching. The probability of switching varies the most with the reliability attribute. High reliability maximizes the chance of staying with the incumbent supplier (the probability of switching is 12.9% for highly reliable suppliers and 54.9% for those with low or average reliability). High reliability and high delivery limit the probability of switching a supplier. Interestingly, while attitude and professionalism was not among major decision factors in the initial supplier selection process, it is predictive for supplier switching given average or low reliability. Specifically, incumbent suppliers with average or low reliability and low attitude and professionalism were the most likely to be switched (72.1% switching probability), while those with average or high attitude and professionalism had a higher chance of staying (49.2% switching probability).

Supplier category, company size, cost and quality were not found to be significant discriminating factors by the CHAID algorithm. The CHAID model correctly classified 70.6% of suppliers. It provides some lift compared to a naïve model that would classify all the suppliers as “not switched” with an accuracy of 64.8%.

Figure 2. *CHAID tree (dependent variable: supplier switching)*



The logit model of switching probability (Model 4 in Table 3) includes all the supplier characteristics that vary in the subsample used for switching modeling (330 suppliers), i.e. all the attributes used in Model 2 with the addition of company size. This model indicates that small, midsize, and large companies are more likely to be switched than the smallest (micro) firms. Cost does not impact switching probability. Average- and high-quality suppliers are less likely to be switched than low-quality suppliers. Similarly, the higher attitude/professionalism and reliability, the lower the probability of switching compared to low levels of these attributes. Finally, high delivery is associated with a lower probability of switching compared to low delivery, whereas average delivery does not give any advantage compared to low delivery. We do not present the results of the extended model containing the full set of dummy variables for departments, as all the department effects turned out to be insignificant according to the likelihood-ratio test ($\chi^2(86)=10.719, p=0.9785$).

Table 3. *Parameter estimates of the logit model of supplier switching (Model 4)*

	Model 4		
	Beta estimate	Std. Error	P-value
Intercept	1.037***	0.168	0.000
company_size: small	0.304***	0.087	0.001
company_size: mid	0.314***	0.086	0.000
company_size: large	0.282***	0.093	0.003
cost: avg	0.023	0.048	0.630
cost: high	-0.052	0.080	0.513
quality: avg	-0.300***	0.100	0.003
quality: high	-0.315***	0.105	0.003
attitude_prof: avg	-0.164***	0.061	0.008
attitude_prof: high	-0.227***	0.065	0.001
reliability: avg	-0.300**	0.118	0.012
reliability: high	-0.649***	0.119	0.000
delivery: avg	0.009	0.088	0.919
delivery: high	-0.140*	0.084	0.096
AIC	*348.7787*		
Log Likelihood	*-159.3894 (df=15)*		
Num. obs.	*330*		

**** - significant at the 1% level,*
*** - significant at the 5% level,*
** - significant at the 10% level*

Overall, based on Model 4, it can be concluded that, controlling for company size, reliability has the largest impact (β_{high}=-0.649), followed by quality (β_{high}=-0.315), attitude and professionalism (β_{high}=-0.227) and delivery (β_{high}=-0.140), while the cost factor is insignificant (β_{high} and β_{avg} are insignificantly different from zero). The difference between each pair of above-mentioned coefficients is statistically significant at the 5% significance level according to formal hypothesis testing of parameter equality. Although the results of the regression analysis do not contradict our conclusions from the CHAID analysis, they additionally acknowledge the role of the quality attribute.

Table A4 in Appendix A provides an overview of the marginal effects, i.e. changes in predicted probability of switching (based on Model 2) as a result of transitioning from the low to the high level of each attribute (except for the statistically insignificant “cost”) holding other attributes constant.

4 Discussion

Overall, CHAID analysis provided a useful diagnosis for constructing the parametric model. Both the initial choice of suppliers and the subsequent switching showed consistency between the CHAID tree algorithm and the logit model. In other words, all the supplier attributes that were expected to have major influence on decision-making based on CHAID analysis turned out to be significant in the parametric model. Our analysis confirms the robustness of CHAID as an efficient classification and diagnosis tool suggested in direct marketing (Elsner, Krafft, and Huchzermeier 2003; Schellinck and Groves 2002). The results of the logit model provide valuable insights into both initial choice and subsequent switching of suppliers, which are discussed in the following.

First of all, it is notable that delivery turned out to be the most important attribute for supplier selection, followed by reliability. This result is consistent with the evolution of the importance of attributes in the supplier selection literature (Verma and Pullman, 1998; Li et al., 2006; Van der Rhee et al., 2009). One possible explanation is that most suppliers have leveled out in terms of the most common factors, such as quality and cost, and that purchasing firms currently use those attributes as screening mechanisms. Furthermore, our results provide an interesting comparison between cost and quality, which has been extensively discussed in the supplier selection literature (Verma and Pullman, 1998). Our revealed preference analysis provides support for the hypothesis that the importance of cost is higher in magnitude compared to quality when it comes to actual decision-making.

We also found out that once the supplier is selected for a constant collaboration, the importance of attributes changes when comparing it to new suppliers. First, cost turns out to be insignificant for switching decisions. This can be explained by the fact that once a supplier has met the required threshold in terms of pricing and other costs, purchasing managers do not give strong consideration to those factors. It is also interesting to note that, in contrast, quality has gained more importance in the switching model compared to the original selection setup. This finding is consistent for both transitions between different quality levels (i.e. from low to average and from low to high).

Another important finding is the increased relevance of the reliability factor. As shown in Table 3, the effect is especially strong when switching from average to high reliability. Given that only constant suppliers are considered for switching in this dataset, it is understandable that the decision-makers might have preferred to have a long-term collaboration with a new, highly reliable supplier. While attitude and professionalism were irrelevant for the initial selection of suppliers, this attribute turned out to be significant in the switching model. An argument can be made that at some point decision-makers start to take intangible criteria such as attitude and professionalism into account when working with a certain suppliers, and switch to a new supplier in order to create a better working environment.

It is also evident that company size did not have a significant role in the initial supplier choice. The switching model, however, indicates that the micro-sized companies had a relatively low probability of being switched. At the same time, there are no significant differences in terms of switching between small, midsize and large companies. The difference between the switching probability for a micro and a larger company in terms of the beta estimates (≈0.3) is similar in magnitude to the difference between suppliers offering average or high quality and those offering low quality (between suppliers with average and low reliability). This implies that micro companies tend to have quite a substantial advantage over their larger counterparts. One possible explanation to this finding is the fact that those are normally boutique companies covering very niche markets, which is why it is more difficult to replace them.

Finally, our results show that there were no significant differences in terms of the supplier selection or switching process in different departments. Most of the decision makers in the company were based in one country, which might have eliminated potential influence of cultural differences on decision-making. Furthermore, during our visits we found out that the company board organizes regular cross-unit meetings between department heads or representatives, to align their respective procurement strategies and discuss major sourcing decisions. This integration across units might have eliminated significant variations between departments. From this perspective, it would be interesting to compare revealed preferred supplier choices between different companies based in different countries. Similar to some of the previous cross-industry/country efforts with stated preference data (Van der Rhee et al., 2009), this would provide insights to preference heterogeneity across both locations and business units.

5 Concluding remarks

This study was designed to analyze the supplier selection and switching process based on revealed preference data. It was aimed at studying how decision-makers tradeoff among cost, quality, delivery, reliability, and attitude and professionalism, given different supplier categories and company sizes. A two-part methodology was proposed consisting of nonparametric CHAID algorithms and logit models. The CHAID decision tree provided an initial classification and diagnosis for constructing the parametric models for initial choice and subsequent switching of suppliers. The CHAID model correctly classified 84.1% of the initial suppliers and 70.6% of switched suppliers, both of which indicate significant improvement compared to a naïve model.

The logit model of supplier choice indicated an absence of heterogeneity across various departments. The results show that delivery plays the most important role in the decision-making process, followed by reliability, cost, and quality. At the same time, managers assign more weight to reliability than delivery once the supplier is selected and a switching decision is to be made. Delivery is somewhat less important with average delivery levels associated with the same risk of being switched and high delivery suppliers being somewhat less often switched than suppliers with lower-level delivery. In addition, the importance of the quality factor increases and cost turns out to be insignificant in the supplier switching process. Cost is not an influential factor of switching presumably because of its objectivity. Once considered acceptable by the buying firm, it is expected to stay unchanged during the whole contract duration, while negative experience due to underperformance in other attributes can be accumulated during the buyer-supplier partnership. Finally, micro-sized companies have a lower probability of being switched from compared to their small, midsize, and large counterparts.

The study is not without its limitations and several aspects could be researched further to validate our findings. First of all, our data includes only representatives of one company based mostly in one location. This setup could be extended to account for potential heterogeneity between different firms, industries, and locations. Another possible direction for future research is the estimation of preferences towards incumbent and new suppliers using more detailed data on choice situations encountered by managers. Such revealed preferences analysis would shed light on supplier-switching inertia and on switching costs that are incurred when changing suppliers.

Overall, the results presented in this paper have important implications for the operations strategy and supply chain management research. To the best of the author's knowledge, this was the first effort in the supplier selection literature to employ discrete choice analysis based on revealed preferred data. Due to its specific nature, this study provides a strong contribution to the existing literature and provokes interest for further research based on actual market data. Building upon the stated preference studies of supplier selection (Verma and Pullman, 1998; Li et al., 2006; Van der Rhee et al., 2009), we provide further insights into the evolution of the importance of attributes in the supplier selection process. Our results support the recent developments implying that suppliers have leveled out in terms of the most common attributes such as quality and cost, forcing purchasing firms to focus on other factors such as delivery and reliability. Furthermore, our results juxtapose cost and quality as two of the most extensively discussed attributes in the supplier selection literature (Verma and Pullman, 1998). This study provides support for the hypothesis that the importance of cost is higher in magnitude compared to quality when it comes to actual decision-making.

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Appendix A

Table A1. *Frequency distributions of supplier characteristics*

	Total sample		Chosen suppliers		Not chosen suppliers	
Variable name and levels	**Column %**	**N**	**Column %**	**N**	**Column %**	**N**
Choice						
Yes (1)	45.5	570	100	570	0	0
No (0)	54.5	683	0	0	100	683
Supplier category						
One-off	8.0	100	8.8	50	7.3	50
Infrequent	18.0	225	19.3	110	16.8	115
Frequent	11.2	140	12.3	70	10.2	70
Constant	61.3	768	57.9	330	64.1	438
Compulsory	1.6	30	1.8	10	1.5	10
Company size						
Micro	14.8	185	14.0	80	15.4	105
Small	27.9	350	27.2	155	28.6	195
Mid	36.6	458	36.8	210	36.3	248
Large	20.8	260	21.9	125	19.8	135
Cost						
Low	23.9	300	36.1	206	13.8	94
Average	50.2	629	50.5	288	49.9	341
High	25.9	324	13.3	76	36.3	248
Quality						
Low	21.9	274	11.8	67	30.3	207
Average	59.1	740	58.8	335	59.3	405
High	19.1	239	29.5	168	10.4	71
Attitude & professionalism						
Low	28.3	354	23.3	133	32.4	221
Average	45.1	565	44.9	256	45.2	309
High	26.7	334	31.8	181	22.4	153
Reliability						
Low	27.2	341	5.6	32	45.2	309
Average	50.4	632	50.9	290	50.1	342
High	22.3	280	43.5	248	4.7	32
Delivery						
Low	36.2	453	7.9	45	59.7	408
Average	32.2	403	32.5	185	31.9	218
High	31.7	397	59.6	340	8.3	57

Table A2. *Marginal effects from changing each attribute's rating from low to high on the probability of selection*

Attribute	**Marginal effect***	**Marginal effect****	**Marginal effect*****
Delivery	13.4%	13.0%	12.2%
Reliability	11.8%	11.3%	10.5%
Cost	-5.5%	-5.2%	-4.1%
Quality	4.2%	4.0%	3.5%

*Notes: *,**,*** indicate low, average, and high levels of all the other attributes, respectively*

Table A3. *Parameter estimates of the logit model of supplier choice with fixed department effects and department-attribute interactions (Model 3)*

	Model 3		
	Beta	Std. Error	P-value
Intercept	-0.541***	0.123	0.000
cost_num	-0.104***	0.030	0.000
quality_num	0.115***	0.031	0.000
attitude_prof_num	-0.002	0.028	0.943
reliability_num	0.195***	0.032	0.000
delivery_num	0.314***	0.025	0.000
department1	-0.313	0.251	0.214
department2	-0.074	0.202	0.714
department3	0.166	0.184	0.367
department4	0.135	0.191	0.481
department5	0.103	0.182	0.573
department6	0.443*	0.235	0.060
department8	0.643	0.472	0.173
cost_num · department1	0.085	0.064	0.180
cost_num · department2	0.062	0.053	0.236
cost_num · department3	-0.042	0.045	0.355
cost_num · department4	-0.002	0.048	0.963
cost_num · department5	0.008	0.043	0.852
cost_num · department6	-0.112*	0.059	0.056
cost_num · department8	-0.178*	0.105	0.092
quality_num · department1	-0.026	0.063	0.675
quality_num · department2	-0.043	0.060	0.472
quality_num · department3	-0.045	0.051	0.379
quality_num · department4	-0.023	0.053	0.668
quality_num · department5	-0.060	0.049	0.223
quality_num · department6	-0.019	0.065	0.775
quality_num · department8	-0.142	0.165	0.388
attitude_prof_num · department1	0.011	0.058	0.849
attitude_prof_num · department2	-0.030	0.050	0.557
attitude_prof_num · department3	-0.008	0.041	0.845
attitude_prof_num · department4	-0.017	0.044	0.703
attitude_prof_num · department5	-0.016	0.042	0.707
attitude_prof_num · department6	-0.083	0.058	0.156
attitude_prof_num · department8	0.053	0.100	0.596
reliability_num · department1	0.102	0.064	0.115
reliability_num · department2	0.058	0.055	0.293
reliability_num · department3	0.054	0.049	0.277
reliability_num · department4	0.054	0.051	0.290
reliability_num · department5	0.068	0.048	0.157
reliability_num · department6	0.059	0.070	0.399
reliability_num · department8	-0.179	0.141	0.205
delivery_num · department1	-0.009	0.055	0.872
delivery_num · department2	-0.014	0.047	0.760
delivery_num · department3	-0.052	0.040	0.195
delivery_num · department4	-0.117***	0.043	0.006
delivery_num · department5	-0.034	0.039	0.374
delivery_num · department6	-0.090	0.055	0.105
delivery_num · department8	0.112	0.124	0.370
AIC		*836.397*	
Log Likelihood		*-399.1985 (df=19)*	
Num. obs.		*1253*	

**** - significant at the 1% level,*
*** - significant at the 5% level,*
** - significant at the 10% level*

Table A4. *Marginal effects from changing each attribute's rating from low to high on the probability of switching*

Attribute	**Marginal effect for a midsize company***	**Marginal effect for a midsize company****	**Marginal effect for a midsize company*****
Reliability	-12.6%	-14.8%	-15.7%
Quality	-5.6%	-6.8%	-7.8%
Attitude and Professionalism	-3.9%	-5.1%	-5.6%
Delivery	-2.4%	-3.2%	-3.5%

*Notes: *,**,*** indicate low, average, and high levels of all the other attributes, respectively*

Appendix B

The constructed logit models can be used to compare the likelihood of choosing and switching a supplier. Two simple examples can illustrate this point. Probability of choosing a supplier, which is a micro company with high cost, high quality, high attitude and professionalism, high reliability, and high delivery (based on β estimates from Model 2 from Table 2) can be computed as follows

- Propensity score Z (utility)=$Intercept+\beta_{\text{cost: high}}+\beta_{\text{quality: high}}+\beta_{\text{attitude\_prof: high}}+\beta_{\text{reliability: high}}+\beta_{\text{delivery: high}}$=0.029-0.220+0.170-0.036+0.482+0.552=0.977
- Prob(chosen)=$e^{0.977}/(1+ e^{0.977})$=0.727, or 72.7%

Probability of being switched for a supplier which is a micro company with high cost, high quality, high attitude and professionalism, high reliability, and high delivery (based on β estimates from Model 4 from Table 3) can be computed as follows

- Propensity score Z (utility)= $Intercept+\beta_{\text{cost: high}}+\beta_{\text{quality: high}}+\beta_{\text{attitude\_prof: high}}+\beta_{\text{reliability: high}}+\beta_{\text{delivery: high}}$ =1.037+-0.052 -0.227-0.649-0.140=-0.346
- Prob(switched)=$e^{-0.346}/(1+exp^{-0.346})$=0.414, or 41.4%

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