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Supplier satisfaction: Explanation and out-of-sample prediction

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ABSTRACT

Many firms not only compete for customers, but increasingly compete for suppliers. Supplier satisfaction is a necessary condition for gaining and maintaining access to capable suppliers and their resources in this new competitive environment. This research replicates and extends the previous empirical research on supplier satisfaction. Additionally, this study tests an extended model for direct and indirect procurement, which assesses antecedents as well as consequences of supplier satisfaction. The findings indicate that next to growth opportunities and reliability, profitability of the relationship has a major impact on supplier satisfaction for both direct and indirect procurement. The results also show that supplier satisfaction has a positive impact on awarding the buyer preferred status, ultimately leading to preferential treatment. An additional exploratory analysis suggests the possibility for a hierarchical model consisting of first- and second-tier antecedents of satisfaction, which are particularly useful in direct procurement. Ultimately, the study provides a guide for purchasers to identify the dimensions of satisfaction to manage for satisfactory buyer–supplier relationships, namely perceived growth opportunity, relational behavior, operative excellence and profitability. The application of the new procedure for creating cross-validated, out-of-sample point predictions reinforces the practical relevance of these findings, which indicates a satisfactory prediction of cases outside the modeling sample.

1. Introduction

In contrast to the classical view of marketing, which assumes a competition for customers, only, research in supplier satisfaction and the preferred customer concept takes the viewpoint of customers competing for capable suppliers. This so-called "reverse marketing" (Leenders & Blenkhorn, 1988, p. 2) recently gains increased attention among supply management scholars (Baxter, 2012). Two main reasons for this phenomenon exist (Schiele, Calvi, & Gibbert, 2012). Firstly, companies, especially in mature markets, reduce their supply base to receive benefits, such as lower transaction costs and larger economies of scale. However, this behavior causes supplier reduction or even supplier scarcity, which can lead to oligopolistic supply market structures (Lavie, 2007; Wagner & Bode, 2011). Secondly, due to increased outsourcing of non-core activities and open innovation initiatives, buying firms are increasingly dependent on their suppliers (Rahmoun & Debabi, 2012; Schiele, 2012).

Therefore, scholars argue that buyers should view the supplier as a key source of competitive advantage and innovation and try to achieve preferred customer status (Schiele, Veldman, & Hüttinger, 2011). However, suppliers have the choice to assign buyers a regular or preferred status (Schiele et al., 2012; Steinle & Schiele, 2008). Buying firms desire to receive preferential treatment over other buyers (Hüttinger, Schiele, & Schröer, 2014). However, the question that emerges in this context is how to become a preferred customer and receive preferential treatment. A necessary condition for achieving preferred customer status could be supplier satisfaction (Hüttinger, Schiele, & Veldman, 2012).

Supplier satisfaction is the buyer's ability to live up to the expectations of the supplier (Schiele et al., 2012), and the relationship between the buyer and supplier influences this satisfaction (Forker & Stannack, 2000). Satisfaction directly links to the quality of the relationship and to value creation. Christiansen and Maltz (2010) reason that being an "interesting" customer to suppliers assures their attention and loyalty. Accordingly, the buyers who can satisfy the suppliers receive the best resources and ultimately a preferred status over other buyers (Hüttinger et al., 2012).

Still, despite such benefits of supplier satisfaction, research in this field is in its infancy. Just since the last decade authors identified critical antecedents and consequences of supplier satisfaction (Hüttinger et al., 2012). Here, researchers increasingly focus on specific relational factors that constitute supplier satisfaction (Essig & Amann, 2009; Ghijsen, Semeijn, & Ernstson, 2010). Most recently, Hüttinger et al. (2014) empirically tested a new model including eight relational antecedents of supplier satisfaction. They are the first researchers to show statistically through partial least squares (PLS) analyses that three significant key antecedents exist in supplier satisfaction: growth opportunity, reliability and relational behavior of the buyer. Despite this advancement, in their study they acknowledge that "[…] the results can hardly be generalized to all industry settings. […] in other industries, other factors or weights could emerge" (Hüttinger et al., 2014, p. 713).

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Therefore, building on research of Hüttinger et al. (2014), the aims of this paper are: (1) To replicate their study in a new context (i.e., indirect procurement); (2) to further extend their analyses by (a) assessing the importance of supplier satisfaction for the buying firm to receive preferred customer status and ultimately preferential treatment and (b) adding an unexplored new antecedent (i.e., profitability) to increase the model's explanatory power; (3) finally, to apply the most up-to-date PLS analyses methods (i.e., PLS-MGA & PLSpredict) to make an evaluation of both the explanatory as well as the predictive performance of the model in the different contexts. After establishing the research background and research aims, the next section will outline the hypotheses of this study.

2. Hypotheses

2.1. Replication: from direct to indirect procurement

A main distinction of products in supply management occurs between direct procurement (direct materials) and indirect procurement (indirect materials) (Chopra & Meindl, 2007). On the one side, direct procurement includes all purchases that are necessary for a company's production process. These are, for example, raw materials or components of the final product. On the other side, indirect procurement includes everything that a company needs to ensure everyday business, but which is not directly related to the production process. This classification includes services and products, such as cleaning services, office supplies and telecommunication equipment (Chopra & Meindl, 2007).

In a typical firm the expenditure for direct materials accounts for about 60% of the total purchasing expenditure (indirect procurement ~40%), whereas direct materials only account for 20%–40% of all purchasing transactions (de Boer, Holmen, & Pop-Sitar, 2003; Neef, 2001). Additionally, predictability and volumes are normally higher in direct procurement and, therefore, require far fewer purchasing transactions than indirect material procurement (Neef, 2001). Correspondingly, the number of transactions and the processing costs relative to the value of each transaction is higher for indirect than for direct procurement (Chopra & Meindl, 2007). Also, indirect procurement usually consists of more non-standardized items purchased in small orders, a larger number of possible suppliers and a wide range of goods and services (de Boer et al., 2003; Nandeesh, Mylvaganan, & Siddappa, 2015). Additionally, buyers have a tendency to communicate less with indirect-material providers, as companies often distribute these purchases and routines and habits frequently dictate purchasing decisions (Ingram, LaForge, Avila, Schwepker, & Williams, 2007; Mosgaard, Riisgaard, & Huulgaard, 2013).

However, despite the substantial share of indirect procurement in the total purchasing expenditures of companies and its distinctiveness to direct procurement, when looking at research efforts, the emphasis of supply management research has traditionally been on direct procurement, since direct procurement is strategically more relevant for firms (Cousins, 1999; Gebauer & Segev, 2001; Kim & Shunk, 2004; Trent & Monczka, 1998). The few studies assessing indirect procurement mainly focus on automatizing indirect procurement transactions through (e-)systems (Batenburg, 2007; Caniato, Golini, Luzzini, & Ronchi, 2010; Lee, Pak, & Lee, 2004) and not on assessing how to manage buyer–supplier relationships. Correspondingly, the consequences of supplier satisfaction in indirect procurement are uncertain, as is the influence of possible antecedents. This research aims to close this gap. For this purpose, this paper replicates and extends the research of Hüttinger et al. (2014), which has only been applied to direct procurement, in the context of indirect procurement to assess the stability of their findings in this new context. The following paragraphs explain the background of their research to form a hypothesis for replication.

The emphasis of Hüttinger et al.'s (2014) research is on the relational antecedents of supplier satisfaction. Their results support theoretical assumptions that the relational behavior and atmosphere in buyer–supplier relationships are important antecedents to supplier satisfaction (Benton & Maloni, 2005; Forker & Stannack, 2000; Hüttinger et al., 2014; Nyaga, Whipple, & Lynch, 2010). More specifically, they use a mixed-methods approach, including focus group interviews and a survey, to identify and test their new model. They further examine seven relational antecedents of supplier satisfaction, which are the buyer's (1) relational behavior, (2) innovation potential, (3) growth opportunity, (4) reliability, (4) operative excellence, (5) involvement, (6) support and (7) access to contacts. After thoroughly assessing the PLS-based analyses, three significant antecedents emerged: growth opportunity, reliability and relational behavior. This study expects that these findings will be the same in the new context of indirect procurement. When replicating the full model with all seven antecedents in both direct and indirect procurement, this study expects that the perceived growth opportunity, reliability and relational behavior positively influence supplier satisfaction, whereas perceived innovation potential, operative excellence, involvement, support and access to contacts are not significant. This reasoning leads to the first hypothesis.

Hypothesis 1. Growth opportunity (H1a), reliability (H1b) and relational behavior (H1c) have a positive impact on supplier satisfaction.

2.2. Extension: profitability, preferred customer status and preferential treatment

In addition to replicating, this study also elaborates on the research of Hüttinger et al. (2014). As stated previously, the main emphasis of their research is on the relational antecedents of supplier satisfaction. Still, several researchers studying channel relationships stress the difference between economic and social perspectives in satisfaction research. They argue that satisfaction constitutes both economic and non-economic aspects (Geyskens, Steenkamp, & Kumar, 1999; Kauser & Shaw, 2004; Nyaga et al., 2010). Scholars like Ruekert and Churchill (1984) even define satisfaction in channel relationships mainly on the basis of a feeling of reward and profitability. Next to relational factors, factors such as profitability and sales growth influence the satisfaction of exchange partners in business-to-business relationships, according to Kauser and Shaw (2004) and Nyaga et al. (2010). Supporting these general notions from the context of channel relationships, scholars specializing in supplier research also argue that both economical and relational aspects are equally important antecedents of supplier satisfaction (Essig & Amann, 2009). Still, Hüttinger et al. (2014) solely take the supplier's growth opportunity into consideration and exclude the profitability of the relationship in their model. Keeping in line with channel and supplier researchers, next to growth potential, the profitability of the relationship is an important factor for suppliers' perceptions of the relationship (Hald, Cordon, & Vollmann, 2009; Hüttinger et al., 2012; Ramsay & Wagner, 2009). Accordingly, this research includes profitability as an additional antecedent of supplier satisfaction and expects that profitability should have a positive impact on supplier satisfaction. More specifically, next to the previously identified antecedents' growth opportunity (H1a), reliability (H1b) and relational behavior (H1c), the profitability of the relationship should have a positive impact on supplier satisfaction.

Hypothesis 2. The perceived profitability of the relationship has a positive impact on supplier satisfaction.

In addition to an assessment of the antecedent of satisfaction, this study further assesses the consequences of supplier satisfaction. As stated earlier, suppliers have the choice to assign buyers a regular or preferred status (Schiele et al., 2012; Steinle & Schiele, 2008). Hüttinger et al. (2012) argue that supplier satisfaction is a necessary condition for achieving such preferred customer status. Scholars

maintain that very satisfied suppliers devote their best resources to the relationship, giving those buyers who can better satisfy them preferred status over other buyers (Hüttinger et al., 2012). Support for this assumption stems from the notion of reciprocity of the social exchange theory, which entails that the more a supplier perceives its expectations to be fulfilled (i.e., satisfaction), the more the same supplier reciprocates these feelings by making relational investments (Nyaga et al., 2010; Pulles, Schiele, Veldman, & Hüttinger, 2016). Conversely, suppliers who are dissatisfied in their relationship tend to invest their resources more in other relationships (Ellegaard & Koch, 2012). Summarized, suppliers who are very satisfied with a buyer should have a higher tendency to give the buyer preferred status (Nollet, Rebolledo, & Popel, 2012; Pulles et al., 2016). Thus, this study expects a positive impact of supplier satisfaction on the supplier's tendency to award the buyer preferred customer status.

Hypothesis 3. Supplier satisfaction has a positive impact on the tendency to award the buyer preferred customer status.

As shown in psychological literature, a distinction exists between intentions to perform a certain behavior and the actual behavior itself. More specifically, theories such as the theory of planned behavior, theory of planned action (Ajzen, 2002) and the protection motivation theory (Rogers, Cacioppo, & Petty, 1983) assume that the intention to engage in a behavior at a specific time and place should be separated from the action itself. Even though Sheeran (2002) views intention as a main predictor of behavior, "People may not always have sufficient control over performing the behavior to actually enact their intentions" (Sheeran, 2002, p. 2). The same distinction can be made in buyer–supplier relationships. Consequently, simply giving preferred customer status (intention) does not necessarily mean that the supplier actually also treats the customer better (behavior). Still, the intention is a significant predictor of action (Sheeran, 2002). This argumentation in part supports previous research assessing the impact of preferred customer status. Several researchers have found that preferred status has a positive impact on gaining access to new technology and better pricing (Ellis, Henke, & Kull, 2012; Schiele et al., 2011; Schiele & Vos, 2015). Therefore, this study proposes that awarding preferred customer status to a buyer has a positive impact on giving preferential treatment to that specific buyer.

Hypothesis 4. Preferred customer status has a positive impact on giving preferential treatment.

Fig. 1 presents the overall research model corresponding to the four hypotheses. The next section continues with an explanation of the outline of the procedures and statistical methods.

3. Material and methods

3.1. Measurement

This study uses multi-item scales to measure the independent and dependent latent factors. The research of Hüttinger et al. (2014) is the basis of this replication study, and the items measuring access to contacts, growth opportunity, innovative potential, reliability, involvement, operative excellence, supplier satisfaction and preferred customer status are identical to those of the Hüttinger et al. (2014) study. This study newly introduces the formative construct "preferential treatment" and the reflective construct "profitability". The measure of preferential treatment comes from the research of Pulles et al. (2016) and includes aspects like sharing the best ideas and employees with the buyer (see Appendix A). The measure of perceived profitability originates with Hald et al. (2009) and Ramsay and Wagner (2009) and includes aspects like the margins achieved and profitability of the buyer–supplier relationship (see Appendix A). A group of twelve practitioners and five supply management scholars first discussed the validity of both preferential treatment and profitability measures. Then, the measures were pre-tested with two waves of random sampling among 1000 key account managers ($N_{(wave\ 1)} = 70$, $N_{(wave\ 2)} = 89$).

Next to the dependent and independent variables of the study, the questionnaire includes an assessment of the characteristics of the suppliers and the supplier–buyer relationship, such as relationship length and supplier size, which are reported in Table 1. This study includes the length of the relationship as a control variable in the model, because previous studies show a significant influence of the length of relationship between buyer and supplier on relational outcomes (Nagati &

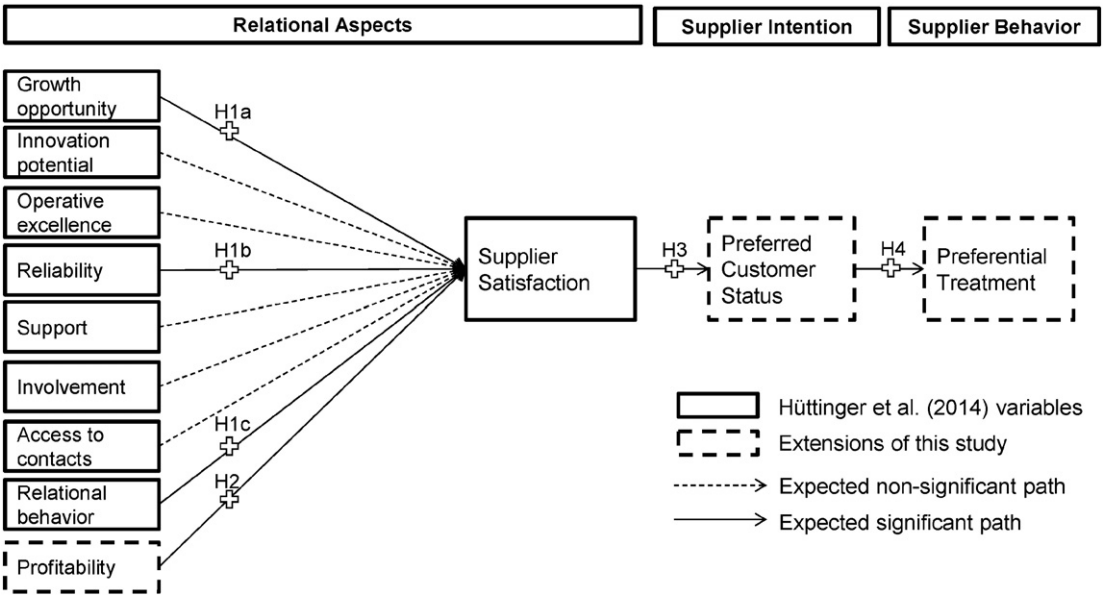

Fig. 1. Research model and hypotheses.

Table 1
Sample and respondent characteristics.

Characteristics of sample			Characteristics of respondents		
	D	I		D	I
1. Length of buying relationship			1. Tenure of respondent in company		
<1 years	1%	0%	<1 years	1%	0%
1–5 years	10%	13%	1–5 years	21%	11%
5–10 years	14%	16%	5–10 years	21%	17%
10–20 years	33%	27%	10–20 years	41%	27%
>20 years	42%	44%	>20 years	16%	45%
2. Annual turnover (in €)			2. Tenure of respondent as sales representative		
<10 m €	14%	28%	<1 years	4%	1%
10 m–100 m €	50%	34%	1–5 years	22%	17%
100 m–1 bn €	24%	23%	5–10 years	32%	26%
>1 bn	12%	15%	10–20 years	34%	33%
			>20 years	8%	23%
3. Number of employees			3. Length of respondent involvement in focal buyer–supplier relationship		
<100	12%	39%	<1 years	2%	1%
100–1000	52%	36%	1–5 years	35%	30%
1000–10,000	23%	14%	5–10 years	31%	22%
10,000–50,000	8%	8%	10–20 years	25%	26%
>50,000	5%	3%	>20 years	7,%	21%

Notes: D = Direct material; I = Indirect material; m = million; bn = billion.

Rebolledo, 2013). Therefore, the analyses control for the effects of length of relationship on supplier satisfaction, preferred customer status and preferential treatment.

3.2. Sampling and data collection

This study uses quantitative data from two German companies. Samplings of both companies collect data from dissimilar contexts. The data on direct material were collected previously from suppliers of an automotive manufacturer by Hüttinger et al. (2014). The data on indirect material come from suppliers of a German chemical company by the authors of this study. For direct procurement, 173 of 2000 suppliers returned valid questionnaires, which is a response rate of 9%. For indirect procurement, the 281 contacted suppliers generated 168 valid questionnaires, which equals a response rate of 62%. Even though a response rate below 10% is not an exception in automotive supply research (Sluis & De Giovanni, 2016), the common response rate usually fluctuates between 15% and 25% (Caniëls, Gehrsitz, & Semeijn, 2013; Corsten, Gruen, & Peyinghaus, 2011; Demeter, Simpson, Power, & Samson, 2007). Therefore, this study compares late versus early respondents among the independent and dependent variables to find potential non-response bias. The comparison between the first quartile (early) and fourth quartile (late) respondents using parametric t-tests and nonparametric Mann–Whitney U tests reveal in total two differences among the variables. Direct procurement shows late respondents experiencing significant higher access to contact ($t_{(90)} = -2.5$, $p = .01$; $U_{(46,46)} = 732$, $p = .01$), whereas in indirect procurement they experience more operative excellence ($t_{(97)} = -2.23$, $p = .03$; $U_{(38,61)} = 857.5$, $p = .03$) compared to the early respondents. All other variables show no significant differences. A control variable in the model includes calculations of the days the respondents needed to respond to the questionnaire to control for the potential effects of non-response bias for operative excellence and access to contacts (Lindner, Murphy, & Briers, 2001).

Finally, after consecutive steps of trimming outliers (see Section 3.4) and respondents who indicated that they do not know the focal companies sufficiently enough (this question was a control question), the final dataset included $N_{(D)} = 171$ for direct (D) and $N_{(I)} = 145$ for indirect (I) procurement. Table 1 shows the distribution of supplier and respondent characteristics of the two samples.

3.3. Choice of statistical analyses

Concerning the *statistical analysis*, either covariance- or partial least squares (PLS)-based statistical analyses are available (Barroso, Carrión, & Roldán, 2010). However, PLS analyses are more flexible to model both reflective and formative latent factors at the same time (Becker, Klein, & Wetzels, 2012; Roldán & Sánchez-Franco, 2012). Additionally, PLS analysis is preferable when the research focus is on predictive rather than explanatory research (Hair, Hult, Ringle, & Sarstedt, 2014; Hair, Ringle, & Sarstedt, 2011). Correspondingly, since the variable "preferential treatment" is a formative latent variable and the focus of this research is on prediction by applying cross validated point-predictions, this study uses PLS path modeling (PLS-PM).

For the application of PLS-PM and significance testing, this study uses the SmartPLS 3.0 software of Ringle, Wende, and Becker (2015). The study also applies the multiple group analysis procedure (PLS-MGA) in SMARTPLS 3.0 for group comparisons (Sarstedt, Henseler, & Ringle, 2011). This PLS-MGA is the non-parametric MGA method of Henseler, Ringle, and Sinkovics (2009), which uses non-parametric bootstrapping in combination with a rank sum test. PLS-MGA compares the path coefficients of two samples and finds significant differences between them. With IBM SPSS 21 (IBM-Corporation, 2012).this study calculates the descriptive statistics and tests for data characteristics, such as common factor loadings, outliers and heteroscedasticity. All analyses handle a significance level of $p < .05$ (one tailed).

Next to statistical inference tests of the causal-explanatory model using PLS-PM, several researchers also call for assessing the predictive performance of PLS models (Armstrong, 2012; Woodside, 2013). Accordingly, the predictive nature of the PLS analyses is facilitated by following the procedures (PLSpredict) of Shmueli, Ray, Velasquez Estrada, & Chatla's (2016-in this issue) to calculate out-of-sample point predictions and prediction errors separately for each item of the outcome variables. The use of 10-fold cross validation distinguishes between training and hold-out sets. For this procedure, the dataset is split into ten parts of randomly selected rows without replacement (Kuhn, 2015), which form the hold-out samples. Subsequently, the data not included in each hold-out set serves as the training sets. The training sets estimate the model and predict the values in the corresponding holdout sets using the PLSpredict function (Shmueli et al., 2016-in this issue). Combining the hold-out sets and their predictions enables the prediction fit statistics to be calculated. Essentially, the assumption is that if a part of the total sample is able to predict another part of the sample, then the model has good predictive capabilities. The authors use the software package R 3.2.2 (R Core Team, 2013) for this procedure. For a more detailed explanation of the PLSpredict procedure see Shmueli et al. (2016-in this issue). The next section describes the findings concerning the data structure and measurement items.

3.4. Quality assessment of data structure, measurement items and latent factors

In a first analysis of the data structure, principal component analysis (PCA) assesses the factor loadings and retains the unique variance of items on their hypothesized components (Petter, Straub, & Rai, 2007). This study applies the default options for Varimax and Oblige (Delta = 0) rotations during the application of PCA, retaining 12 components. The minimum cut-off loading is .50, because this value is between the recommendations of .45 for sample sizes >150 (Hair, Anderson, Tatham, & Black, 1998) and .55 for "good loadings" regardless of sample sizes (Tabachnick & Fidell, 2007). After consecutive steps of trimming, the final results show unique loadings of items on the corresponding components of >.50 for all Varimax solutions and for the majority of Oblique rotations.

Additionally, all communalities per item are above .60 (on average even above .70), which is the recommended value for smaller sample sizes (MacCallum, Widaman, Preacher, & Hong, 2001).

Also this study further analyzes the data characteristics in terms of linearity, independence of residuals, heteroscedasticity and outliers. These calculations include the latent factor scores of all items calculated in SMARTPLS 3.0 and exported back to SPSS. The visual assessment using scatter dot diagrams and fitting lines show that the effects of the independent variables on the dependent variables are all closest to linear functions. When regressing the eight antecedents (see Fig. 1) on satisfaction, the test reveals that the residuals are independent (Durbin Watson tests, $DW_I = 1.93 > 1$ & $DW_D = 1.86 > 1$) and the distributions of residuals depart from normality only for indirect procurement (Shapiro Wilk Test, $W_{I(156)} = .952$; $p = 0.001$ & $W_{D(173)} = .990$; $p = 0.271$) (Field, 2009). The Koenker test (Godfrey, 1996) reveals possible heteroscedasticity for indirect procurement, but not for direct procurement (I: $\chi^2_{(df=10)} = 19.71$, $p = .03$; D: $\chi^2_{(df=10)} = 17.62$, $p = .06$), meaning that in indirect procurement the model shows signs of asymmetric relationships (Woodside, 2013) as the model explains the variance better (i.e., has smaller residuals) for higher values of supplier satisfaction than for lower values. Concerning outliers, the Maximum Mahalanobis Distances (max > 16.91) and Centered Leverage Values ($max_I > .116$ & $max_D > .104$) diagnose extreme values in the data (Field, 2009). For identifying the specific outliers among the latent variable scores this study uses the Outlier Labeling Rule (Hoaglin, Iglewicz, & Tukey, 1986) with a g-value of 2.2 (Hoaglin et al., 1986). Eleven outliers for indirect and two outliers for direct procurement with extreme scores emerged. Further analyses were not conducted on these 13 excluded cases (listwise deletion).

Furthermore, the unmeasured latent method factor test (Podsakoff, MacKenzie, Lee, & Podsakoff, 2003) reveals that for both datasets the means of squared method factor loadings are below .01 and the means of squared construct loadings are above .76. This result signifies that the large ratio of substantive loading variance to method variance (76:1) of the unmeasured latent methods factor test indicates that common method bias is unlikely to be an issue in the data.

Concerning the quality criteria of the latent factors, firstly, the tests relating to convergent validity show Cronbach's alpha (α) and Composite Reliability (CR) scores above a threshold of .70 (Bagozzi & Yi, 1988; Field, 2009) and Average Variances Extracted (AVE) of greater than .50 (see Table 2). Support for the discriminant validity is threefold: (I) The Variance Inflation Factors (VIF) of the variables in the datasets are below 2.5, so no substantive high VIF values are existent (Diamantopoulos & Siguaw, 2006; Pan & Jackson, 2008). (II) The Fornell and Larcker (1981) procedure shows that no correlation higher than √AVE exists (see Table 2). (III) The analyses concerning the heterotrait–monotrait ratio (HTMT) show that for both direct and indirect procurement the HTMT matrix values have a maximum of .77 ($HTMT_{(D)} \leq .77$; $HTMT_{(I)} \leq .69$) and are, therefore, below a maximum threshold of .85 (Henseler, Ringle, & Sarstedt, 2015). Also, the HTMT bootstrapping analysis of the upper confidence intervals indicates no values above 1.0 ($CI95\text{-}HTMT_{(D)} \leq .86$; $CI95\text{-}HTMT_{(I)} \leq .82$). After testing these data characteristics, the next section takes a closer look at the quality criteria of the entire PLS model.

3.5. Assessment of the quality criteria of the models

A blindfolding procedure (omission distance of 4) (Hair et al., 2011; Henseler et al., 2009) assesses the overall predictive relevance of the model as a first step in the quality assessment. The analyses reveal Stone–Geisser Q^2 values ranging from .12 to .34 for cross-validated redundancies and from .31 to 1.00 for cross-validated communalities. This finding provides strong support for the model's overall predictive relevance, since the Q^2 values are clearly above 0 (Henseler et al., 2009).

As a second quality assessment this study assesses the standardized root mean square residual (SRMR) goodness of fit (GoF) indicators for the models. A value less than .10 or even 0.08 reflects a good fit (Henseler et al., 2014). Additionally, the SRMR value should be below

Table 2
Cross-correlations and quality criteria of constructs.

Constructs		1	2	3	4	5	6	7	8	9	10	11	12	13	14
1	Access to contacts	–	.21	.11	.09	.11	−.11	.40	.20	.12	.10	.32	.41	.33	.22
2	Growth potential	.32	–	.59	.25	−.01	−.02	.32	.41	.37	.38	.49	.36	.43	.46
3	Innovation potential	.26	.31	–	.41	−.03	−.06	.41	.35	.30	.37	.45	.23	.25	.52
4	Involvement	.38	.23	.46	–	.00	.05	.42	.39	.19	.26	.42	.27	.24	.50
5	Days to respond	.10	.07	−.02	.04	–	.05	.18	−.02	−.09	.04	−.02	−.04	.04	.00
6	Length of relationship	.03	.08	.21	.17	−.03	–	−.07	.14	.08	−.10	.02	−.03	.04	−.07
7	Operative excellence	.40	.22	.22	.17	.11	−.22	–	.30	.23	.32	.56	.40	.45	.42
8	Preferential treatment	.22	.20	.20	.23	−.08	.01	.19	–	.52	.21	.36	.28	.43	.30
9	Preferred status	.15	.48	.20	.13	−.04	.12	.13	.54	–	.23	.35	.31	.41	.23
10	Profitability	.40	.47	.30	.21	.04	−.09	.49	.13	.31	–	.41	.32	.48	.27
11	Relational behavior	.47	.42	.32	.32	.09	−.01	.54	.24	.24	.61	–	.57	.50	.49
12	Reliability	.46	.32	.23	.16	.06	−.13	.56	.18	.29	.57	.66	–	.57	.40
13	Supplier satisfaction	.42	.48	.33	.26	.02	.03	.49	.14	.41	.69	.68	.64	–	.31
14	Support	.33	.34	.45	.39	.05	.01	.38	.25	.25	.37	.46	.37	.36	–
Quality criteria															
D	AVE	.83	.59	.82	.77	–	–	.68	–	.72	.83	.85	.77	.78	.79
D	√AVE	.91	.77	.90	.88	–	–	.82	–	.85	.91	.92	.88	.88	.89
D	CR	.94	.85	.93	.93	–	–	.89	–	.91	.94	.92	.93	.95	.92
D	Cronbach's alpha	.90	.77	.89	.90	–	–	.85	–	.87	.90	.82	.90	.93	.87
D	Highest VIF	1.6	1.4	1.5	1.5	1.0	1.2	1.8	–	1.0	2.0	2.5	2.2	1.0	1.6
I	AVE	.78	.67	.86	.86	–	–	.75	–	.76	.86	.85	.69	.74	.86
I	√AVE	.88	.82	.93	.93	–	–	.86	–	.87	.92	.92	.83	.86	.93
I	CR	.92	.89	.95	.96	–	–	.92	–	.93	.95	.92	.90	.93	.95
I	Cronbach's alpha	.86	.84	.92	.95	–	–	.89	–	.89	.92	.82	.85	.91	.92
I	Highest VIF	1.4	1.8	2.0	1.6	1.1	1.1	1.9	–	1.0	1.4	2.3	1.7	1.0	1.8

Notes: Left correlation block contains correlations of direct material (D) and right correlation block contains correlations of indirect materials (I); D = direct procurement; I = indirect procurement; AVE = Average Variance Extracted; CR = composite reliability; √AVE = value for assessing the Fornell and Larcker (1981) statistic of discriminant validity (Criterion = √AVE > r); AND VIF = variance inflation factor.

Table 3
Bootstrap and effect statistics of the models (bootstrap samples = 5000).

Paths	β	SE	t	f^2	β	SE	t	f^2	DIFFMGA
	D	D	D	D	I	I	I	I	D|I
CA ≥ SS	.00	.06	.03	.00	.06	.07	.92	.01	.06
G ≥ SS	.13	.06	2.29*	.03	.20	.08	2.47**	.04	.07
IP ≥ SS	.05	.06	.87	.00	−.12	.07	1.60	.01	.17
I ≥ SS	.02	.06	.37	.00	−.02	.06	.28	.00	.04*
O ≥ SS	.07	.06	1.11	.01	.20	.08	2.51**	.04	.13
P ≥ SS	.33	.06	5.24**	.15	.28	.06	4.38**	.11	.05
RB ≥ SS	.25	.08	3.26**	.07	.05	.10	.47	.00	.20
R ≥ SS	.23	.06	3.93**	.06	.32	.08	3.93**	.12	.10
S ≥ SS	−.06	.06	1.00	.01	−.03	.07	.42	.00	.03
DR ≥ SS	−.05	.05	.93	.01	.00	.07	.03	.00	.05
L ≥ PT	−.06	.08	.74	.00	.10	.07	1.35	.01	.16
L ≥ PC	.11	.07	1.51	.01	.06	.07	.87	.00	.05
L ≥ SS	.08	.05	1.53	.01	.09	.06	1.59	.02	.01
SS ≥ PC	.41	.07	5.62**	.20	.41	.08	5.16**	.20	.00
PC ≥ PT	.55	.06	9.74**	.42	.51	.06	8.57**	.36	.04

Notes: D = direct procurement; I = indirect procurement; β = standardized coefficient beta; t = t-statistic; SE = standard error of β; f^2 = effect size of variance explained by predictor; DIFFMGA = difference in the multi-group analyses between direct and indirect procurement; * = p < .05 (one-sided); ** = p < .01 (one-sided); CA = contact accessibility; G = growth opportunity; I = involvement; IP = innovative potential; DR = days to respond to the questionnaire (Control); O = operational excellence; P = profitability; RL = reliability; treatment RB = relational behavior; S = support; L = length of relationship (Control); SS = supplier satisfaction; PC = preferred customer status; and PT = preferential treatment.

the SRMR's upper confidence interval (97.5%). The next section presents the corresponding results for these analyses, together with the results of the PLS-PM and MGA analyses.

Thirdly, calculations of several scale independent fit indices measure the accuracy of the 10-fold, out-of-sample point predictions and allow a comparison of the models. This study calculates the mean absolute percentage error (MAPE) (Hora & Campos, 2015) as well as Theil's (1966) U-statistics, namely U_1 (forecast accuracy), U_2 (forecast quality) and the mean square error decompositions (U^M, U^R and U^D) (Hora & Campos, 2015; Watson & Teelucksingh, 2002). Like the SRMR, these model-specific indices are also not reported here, but in the following Results section.

4. Results

4.1. Findings of the replication and extension of the original model

The results of the PLS-PM analyses (Table 3 and Fig. 2) show, firstly, that concerning Hypotheses 1a–d and 2 the datasets show slightly differing results (Table 3, Fig. 2). The analyses of direct procurement reveals that growth opportunity (H1a; t = 2.29, β = .13, f^2 = .03), reliability (H1b; t = 3.93, β = .23, f^2 = .06), relational behavior (H1c; t = 3.26, β = .25, f^2 = .07) and profitability (H2; t = 5.24. β = .33, f^2 = .15) indeed have a positive impact on supplier satisfaction. However, in the context of indirect procurement, growth opportunity (H1a; t = 2.47, β = .20, f^2 = .04), reliability (H1b; t = 3.93, β = .32, f^2 = .12), profitability (H2; t = 4.38, β = .28, f^2 = .11), but not relational behavior (H1c; t = .47, β = .05, f^2 = .00) appear significant. Therefore, although relational behavior has a positive impact on supplier satisfaction in direct procurement, this effect vanishes in indirect procurement. Additionally, the findings show that operative excellence positively impacts supplier satisfaction in indirect procurement (t = 2.51, β = .20, f^2 = .04). Also, the overall explanatory power of the antecedents to explain the variance in supplier satisfaction is higher in direct procurement (R^2 = .64) than in indirect procurement (R^2 = .50). When comparing the relational with the economical antecedents, both explain similar variances in supplier satisfaction in direct ($f^2_{(relational)}$ = .13; $f^2_{(economical)}$ = .18) and indirect ($f^2_{(relational)}$ = .16; $f^2_{(economical)}$ = .15) procurement.

Concerning Hypothesis 3, the data supports the assumption that supplier satisfaction has a positive impact on the tendency to award the buyer preferred customer status in both direct (H3; t = 5.62, β = .41, f^2 = .20) and indirect procurement (H3; t = 5.16, β = .41, f^2 = .20). Also, Hypothesis 4, which supposes that preferred customer status, has a positive impact on preferential treatment. The findings support this hypothesis (H4; $t_{(D)}$ = 9.74, $\beta_{(D)}$ = .55, $f^2_{(D)}$ = .42; $t_{(I)}$ = 8.57, $\beta_{(I)}$ = .51, $f^2_{(I)}$ = .36). The variances explained in awarding preferred status ($R^2_{(D)}$ = 18; $R^2_{(I)}$ = 17) and in receiving preferential treatment ($R^2_{(D)}$ = 30; $R^2_{(I)}$ = 28) are almost equal for both direct and indirect procurement.

Furthermore, when comparing the model of the two datasets using the PLS-MGA algorithm (see Table 3), significant differences between

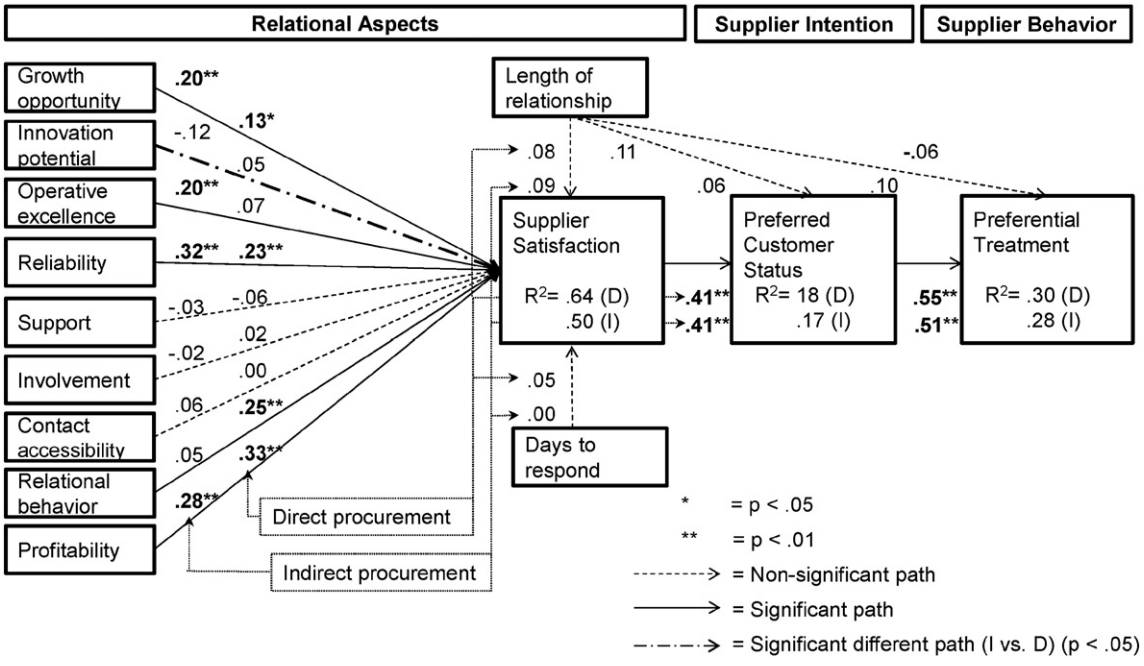

Fig. 2. Results of PLS-PM for direct (D) and indirect (I) procurement.

Table 4
SRMR Results of the Composite Models (Bootstrap samples = 5000).

	Original model			Revised model		
	SRMR	CI 2.5%	CI 97.50%	SRMR	CI 2.5%	CI 97.50%
Direct procurement	.066	.071	.090	.066	.071	.091
Indirect procurement	.059	.069	.088	.059	.068	.087

Notes: SRMR = standardized root mean square residual; and CI = confidence interval.

the datasets concerning the effects of innovation potential ($\beta_{(D)}$- $\beta_{(I)}$ = .17, $p < .04$) on supplier satisfaction exist. Still, the path coefficient to satisfaction is not significant for innovation potential and, therefore, further discussions neglect this effect.

In relation to the goodness of fit indices (Table 4), the model shows a good model fit with SRMR values below .08 ($SRMR_{(D)}$ = .066; $SRMR_{(I)}$ = .059). Concerning the 10-fold cross validated out-of-sample predictions (see Table 5), the model predicts the hold-out samples better than a naive no-change forecast with $U_2 < 1$ ($U_{2(D)}$ = .29; $U_{2(I)}$ = .17). Additionally, the hold-out samples are better predicted in indirect procurement than in direct procurement with lower values of MAPE, U_1, U_2 ($MAPE_{(D)}$ = .32 vs. $MAPE_{(I)}$ = .17; $U_{1(D)}$ = .15 vs. $U_{1(I)}$ = .09; $U_{2(D)}$ = .29 vs. $U_{2(I)}$ = .17). Still, when looking at the distribution of bias, regression and disturbance proportions of the MSE, the model better predicts the systematic error (disturbance proportion) in indirect procurement ($U^D_{(D)}$ = .78 vs. $U^D_{(I)}$ = .83). Summarized, in both direct and indirect procurement the model shows sufficient as well as similar explanatory and predictive performances.

4.2. Improvement of the original model

Ozkan and Kanat (2011) state that the standard procedure when using PLS-PM is to first formulate a research model grounded in theory or previous findings, and then modify this model according to the results. For cases in which a model shows room for improvement, the researchers modify the original model by taking changes in the model's fit, R^2 values, bootstrap t-test results and path loadings into account (Blunch, 2008; Ozkan & Kanat, 2011). Also, in these circumstances, the SRMR is a valuable guide to determine model fit changes (Henseler & Sarstedt, 2013). All changes are a careful assessment of theory and logical reasoning, rather than purely statistical changes (Ozkan & Kanat, 2011). Accordingly, this study analyzed the model of Hüttinger et al. (2014) in-depth to find possible improvements.

Table 5
Fit indices of point predictions for the original model.

Item	Direct procurement						Indirect procurement					
	MAPE	U_1	U_2	U^M	U^R	U^D	MAPE	U_1	U_2	U^M	U^R	U^D
SS1	.29	.13	.25	.00	.01	.99	.12	.07	.14	.00	.02	.98
SS2	.37	.15	.29	.00	.01	.99	.09	.05	.10	.00	.00	1.00
SS3	.28	.12	.25	.00	.00	1.00	.09	.05	.10	.00	.00	1.00
SS4	.23	.11	.21	.00	.00	1.00	.07	.04	.09	.00	.00	1.00
SS5	.24	.11	.21	.00	.01	.99	.11	.06	.12	.00	.00	1.00
PC1	.30	.14	.27	.00	.08	.92	.14	.08	.16	.00	.13	.87
PC2	.30	.14	.28	.00	.18	.82	.15	.08	.16	.00	.19	.81
PC3	.33	.15	.30	.00	.22	.78	.14	.08	.16	.00	.17	.83
PC4	.35	.15	.30	.00	.21	.79	.15	.08	.16	.00	.12	.88
PT1	.38	.18	.36	.00	.49	.51	.14	.08	.16	.00	.31	.69
PT2	.32	.17	.33	.00	.42	.58	.18	.10	.19	.00	.33	.67
PT3	.39	.19	.38	.00	.51	.49	.35	.16	.31	.00	.32	.68
PT4	.35	.17	.35	.00	.50	.50	.36	.15	.31	.00	.38	.62
PT5	.31	.16	.32	.00	.45	.55	.26	.13	.26	.00	.43	.57
Averages	.32	.15	.29	.00	.22	.78	.17	.09	.17	.00	.17	.83

Notes: MAPE = mean absolute percentage error; U_1 = Theil's forecast accuracy; U_2 = Theil's forecast quality; U^M = bias proportion of MSE; U^R = regression proportion of MSE; U^D = disturbance proportion of MSE; SS = supplier satisfaction; PC = preferred customer status; and PT = preferential treatment.

Fig. 3 shows that this study identifies the possibility to order the factors into first- and second-tier antecedents of satisfaction. The model in particular includes the interrelations of antecedents.

As previously described, both economic and relational factors are critical to supplier satisfaction (Hüttinger et al., 2012). Therefore, the first-tier antecedents, which are directly linked to satisfaction, are growth opportunity, profitability, relational behavior and operative excellence. On the one hand, the first tier consists of the growth opportunity and profitability, because they reflect the economic value of the relationship (Hald et al., 2009; Hüttinger et al., 2012; Ramsay & Wagner, 2009). In relation to growth opportunity, suppliers who perceive innovative potential of a buyer (second-tier antecedent) also perceive a higher growth potential, since more innovative companies are associated with stronger market growth (Audretsch, Coad, & Segarra, 2014). Correspondingly, innovative potential is a predictor of perceived growth potential in the revised model.

On the other hand, second only to economic factors, relationship behavior and operative excellence are first-tier, because they reflect an overall cooperative and professional supply chain strategy (Nyaga et al., 2010). *Relational behavior* contains aspects, such as openness and reciprocity, which both develop over time (Forker & Stannack, 2000). Sequentially, perceived relational behavior also mirrors the buyer's *reliability* and *support* as well as active *involvement* of the supplier in the buyer's processes (Essig & Amann, 2009; Ghijsen et al., 2010). Next to relational behavior, *operative excellence* is an important factor in supplier satisfaction. In particular low-levels of operative excellence (i.e., slow order processing and billing/delivery procedures) often hinder satisfactory business transactions and can be detrimental to supplier satisfaction (Essig & Amann, 2009). In turn, the perception of operative excellence can influence the degree to which the supplier can *access the buyer's contacts*. When a supplier has a specific contact person who cares for the relationship and coordinates activities (Essig & Amann, 2009), the supplier also perceives a higher degree of operational excellence of the buying firm, since questions and operational problems can be addressed directly to such a contact person. Conclusively, the revised model comprises growth potential, relational behavior, operative excellence & profitability as first tier, and involvement, reliability, support and access to contacts as second-tier antecedents. The next section explains the findings concerning this new model.

4.3. Findings of the revised model

In accordance with the recommendation of Henseler and Sarstedt (2013), this study compares the two models on the basis of path coefficients and significances. In the new model, all but the three paths from the control variable relationship length are significant among both datasets (Table 6, Fig. 3), as opposed to only six significant (eight non-significant) paths in the original model. Also, the overall β and f^2 values increase in the revised model. More precisely, the average β increases from .14 to .24 and the average f^2 increases from .6 to .13 (see Tables 3 and 5), indicating a potentially higher explanatory power of the constructs in the revised model. However, as an adverse change, the antecedents in indirect procurement explain less the variance of supplier satisfaction ($R^2_{(original\ model)}$ = .50; $R^2_{(revised\ model)}$ = .39) than in the original model. Thus, even though the average f^2 values of the model increase, the explanatory power concerning supplier satisfaction decreases. Placing reliability as a second-tier factor in the revised model comes at the price of a reduced R^2 value in supplier satisfaction for indirect procurement.

The comparison between direct and indirect procurement in the revised model reveals that innovation potential has a significant, different effect. More specifically, the path from innovation potential to growth opportunity ($\beta_{(D)}$- $\beta_{(I)}$ = −.29, $p < .01$.) is significantly different for the two procurement practices. The perceived innovation potential is

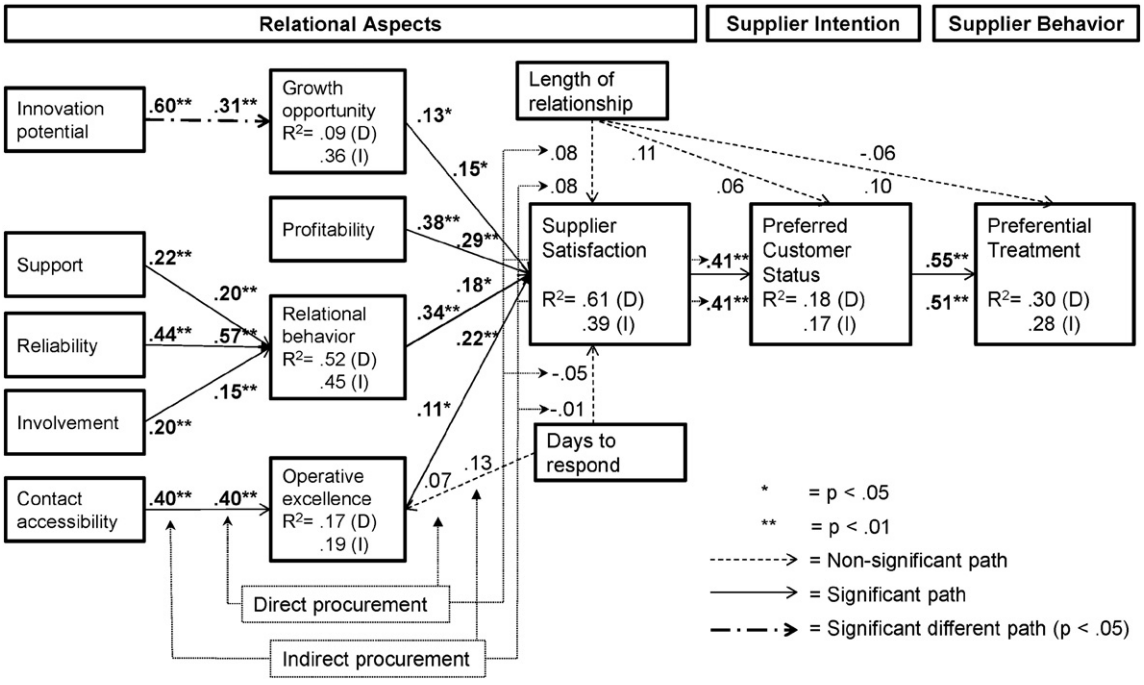

Fig. 3. Results of PLS-PM of the revised model for direct (D) and indirect (I) procurement.

significantly more important in indirect procurement for perceiving growth potential of the buyer than in indirect procurement.

In terms of fit and prediction outcomes, the original and the revised models have equal SRMRs (direct procurement: $SRMR_{(original\ model)} = .066$ vs. $SRMR_{(revised\ model)} = .066$; indirect procurement: $SRMR_{(original\ model)} = .059$ vs. $SRMR_{(revised\ model)} = .059$). Concerning the predictive performance, for example, in the original model, the results of the 10-fold cross-validated point predictions for the revised model (Table 7) indicate that direct and indirect procurement are both better predicted than the naive no-change forecast with $U_2 < 1$ ($U_{2(D)} = .31$; $U_{2(I)} = .23$). Also, the model better predicts the hold-out samples indirect procurement than in direct procurement ($MAPE_{(D)} = .35$, $MAPE_{(I)} = .25$). Additionally, Tables 5 and 7 show the decomposition of the mean square error into Theil's bias (U^M), regression (U^R) and disturbance (U^D) proportions. Here, the revised model better explains the systematic disturbance in the MSE better than the original model (direct procurement: $U^D_{(original\ model)} = .78$ vs. $U^D_{(revised\ model)} = .83$; indirect procurement: $U^D_{(original\ model)} = .83$ vs. $U^D_{(revised\ model)} = .85$). Summarized, the comparison between the original and revised models shows that even though the revised

Table 6
Bootstrap and effect statistics of the revised models (bootstrap samples = 5000).

Paths	β	SE	t	f^2	β	SE	t	f^2	DIFFMGA
	D	D	D	D	I	I	I	I	D|I
IP ≥ GP	.31	.07	4.64**	.10	.60	.06	1.81**	.56	.29*
S ≥ RB	.20	.06	3.32**	.06	.22	.08	2.64**	.06	.02
R ≥ RB	.57	.06	10.00**	.58	.44	.08	5.19**	.29	.13
I ≥ RB	.15	.06	2.68**	.04	.20	.08	2.52**	.06	.05
CA ≥ O	.40	.07	6.20**	.20	.40	.08	5.10**	.20	.00
G ≥ SS	.13	.05	2.33*	.03	.15	.09	1.71*	.03	.03
P ≥ SS	.38	.06	6.14**	.19	.29	.06	4.68**	.11	.08
RB ≥ SS	.34	.07	5.00**	.15	.18	.10	1.83*	.03	.16
O ≥ SS	.11	.06	1.79*	.02	.22	.08	2.74**	.05	.10
DR ≥ O	.07	.07	.94	.01	.13	.08	1.63	.02	.06
DR ≥ SS	−.05	.05	.98	.01	−.01	.07	.09	.00	.05
L ≥ PT	−.06	.07	.79	.00	.10	.08	1.33	.01	.16
L ≥ PC	.11	.07	1.54	.01	.06	.07	.87	.00	.05
L ≥ SS	.08	.05	1.46	.01	.08	.06	1.38	.01	.01
SS ≥ PC	.41	.07	5.46**	.20	.41	.08	5.22**	.20	.00
PC ≥ PT	.55	.06	9.68**	.42	.51	.06	8.53**	.36	.04

Notes: D = direct procurement; I = indirect procurement; β = standardized coefficient beta; t = t-statistic; SE = standard error of β; f2 = effect size of variance explained by predictor; DIFFMGA = difference in the multi-group analyses between direct and indirect procurement; * = p < .05 (one-sided); ** = p < .01 (one-sided); CA = contact accessibility; G = growth opportunity; I = involvement; IP = innovative potential; DR = days to respond to the questionnaire (Control); O = operational excellence; P = profitability; RL = reliability; treatment RB = relational behavior; S = support; L = length of relationship (Control); SS = supplier satisfaction; PC = preferred customer status; and PT = preferential treatment.

Table 7
Fit indices of point predictions for the revised model.

Item	Direct procurement						Indirect procurement					
	MAPE	U_1	U_2	U^M	U^R	U^D	MAPE	U_1	U_2	U^M	U^R	U^D
G1	.28	.14	.29	.00	.26	.74	.35	.16	.32	.00	.41	.59
G2	.24	.12	.25	.00	.33	.67	.26	.13	.27	.00	.29	.71
G3	.43	.18	.36	.00	.30	.70	.59	.24	.48	.00	.37	.63
G4	.32	.16	.31	.00	.35	.65	.49	.21	.41	.00	.36	.64
O1	.48	.21	.43	.00	.36	.64	.36	.18	.35	.00	.39	.61
O2	.46	.21	.41	.00	.31	.69	.42	.20	.39	.00	.41	.59
O3	.51	.22	.44	.00	.32	.68	.46	.20	.39	.00	.28	.72
O4	.49	.22	.43	.00	.27	.73	.39	.17	.35	.00	.28	.72
RB1	.42	.18	.35	.00	.26	.74	.20	.10	.20	.00	.06	.94
RB2	.43	.18	.34	.00	.19	.81	.21	.10	.21	.00	.08	.92
SS1	.33	.14	.28	.00	.15	.85	.13	.07	.15	.00	.05	.95
SS2	.40	.17	.32	.00	.14	.86	.10	.05	.11	.00	.01	.99
SS3	.30	.13	.26	.00	.07	.93	.10	.05	.11	.00	.02	.98
SS4	.26	.12	.23	.00	.08	.92	.08	.04	.09	.00	.01	.99
SS5	.26	.11	.22	.00	.04	.96	.12	.06	.13	.00	.03	.97
PC1	.34	.14	.28	.00	.10	.90	.13	.08	.16	.00	.05	.95
PC2	.32	.14	.27	.00	.03	.97	.14	.08	.15	.00	.08	.92
PC3	.33	.14	.28	.00	.01	.99	.14	.07	.15	.00	.06	.94
PC4	.35	.14	.28	.00	.03	.97	.15	.08	.16	.00	.09	.91
PT1	.32	.14	.27	.00	.13	.87	.13	.07	.14	.00	.07	.93
PT2	.29	.13	.27	.00	.06	.94	.16	.08	.17	.00	.05	.95
PT3	.31	.14	.29	.00	.10	.90	.31	.13	.26	.00	.04	.96
PT4	.29	.13	.26	.00	.09	.91	.31	.13	.25	.00	.06	.94
PT5	.26	.13	.25	.00	.05	.95	.21	.10	.21	.00	.09	.91
Averages	.35	.16	.31	.00	.17	.83	.25	.12	.23	.00	.15	.85

Notes: MAPE = Mean absolute percentage error; U_1 = Theil's forecast accuracy; U_2 = Theil's forecast quality; U^M = bias proportion of MSE; U^R = regression proportion of MSE; U^D = disturbance proportion of MSE; G = growth opportunity; O = operational excellence; RB = relational behavior; SS = supplier satisfaction; PC = preferred customer status; and PT = preferential treatment.

model has more significant paths and a higher average f^2, the revision has a similar goodness of fit and predictive performance when compared to the original. Also, both models predict supplier satisfaction better in indirect procurement than in direct procurement. The next section further discusses the findings of this study.

5. Discussion and implications

5.1. Discussion

The goal of this paper is to replicate and extend the existing research and provide a more fine-grained picture of the antecedents and consequences of supplier satisfaction. The findings show that growth opportunity, reliability and profitability are relevant antecedents of supplier satisfaction regardless of the product context. Here, indirect procurement successfully replicates the model. Additionally, the results support the new hypothesis that the profitability of the relationship could be a valuable extension to the original model of Hüttinger et al. (2014). Surprisingly, the positive impact of relational behavior on supplier satisfaction is only significant in the context of direct procurement. This finding is unexpected, since positive relational behavior, such as a collaborative supply chain strategy, should have a positive influence on the satisfaction of suppliers (Essig & Amann, 2009; Nyaga et al., 2010). As a possible explanation, inter-correlated antecedents, such as the buyer's reliability and support, might suppress the statistical effects of the buyer's relational behavior on supplier satisfaction. During the search for a model that takes the interdependencies between the antecedents of satisfaction into account, this study established the revised model of supplier satisfaction. Theoretical reasoning indicates that certain antecedents might precede and influence others, thereby proposing the revised model and a clearer distinction among economic, relational and operative factors. Within the revised model, at the first tier, (1) profitability, (2) growth opportunity, (3) relational behavior and (4) operative excellence directly impact supplier satisfaction. At the second tier, (2a) innovation potential has a positive impact on growth potential; (3a) support, (3b) reliability and (3c) involvement positively affect relational behavior; and (4a) contact accessibility has a positive impact on perceived operative performance. The results after applying PLS-PM, PLSMGA and PLSpredict show that, compared to the original model, the revised model has a higher number of significant paths and a greater overall f^2/R^2, but a reduced explanatory power of supplier satisfaction in the context of indirect procurement. The existence of an asymmetric relationship between antecedents and supplier satisfaction in indirect procurement might lead to these results, as the model is less accurate in explaining the variance (i.e., larger residuals) for lower values of supplier satisfaction.

In addition to the assessment of the antecedent of satisfaction, this study assesses the consequences of supplier satisfaction. In detail, the findings confirm previous elaborations by Pulles et al. (2016) and Nollet et al. (2012) that supplier satisfaction has a positive impact on the tendency to award preferred customer status, which in turn leads to preferential treatment. In other words, suppliers who are very satisfied with a buyer have a higher tendency to give the buying firm preferred status and ultimately treat the firm better than its competitors. The following section addresses the implications of the findings.

5.2. Implications and future research directions

The practical implications of this study are twofold. Firstly, the findings show that supplier satisfaction is a means to gain a competitive advantage, because supplier satisfaction positively impacts the supplier's tendency to award preferred customer status, and ultimately give preferential treatment to buyers. Hence, as proposed by Pulles et al. (2016), supplier satisfaction is a means to gain competitive advantages over supply-market competitors in direct and indirect procurement. Secondly, the common belief that economic factors are much more important to suppliers than relational factors is misleading. The findings of this study show that among both models (i.e., original and revised models) and procurement practices (i.e., direct and indirect procurement), relational factors, such as relational behavior, reliability and operative excellence, explain similar or even greater variance in supplier satisfaction than economic factors like profitability and growth potential. In other words, even when buyers cannot offer a large economic value to suppliers, these buyers can still influence the suppliers' satisfaction and receive preferential treatment by being reliable, operationally excellent and presenting good relational behavior. The questionnaire items underlying each dimension (see Hüttinger et al., 2014) can be a guide for practitioners to focus activities aimed at improving satisfaction. For example, for achieving increased operative excellence, buyers should focus on timely and correct forecasts (see Hüttinger et al., 2014). In this way, practitioners can use the findings to better adjust their relational efforts.

In addition to the practical implications, the theoretical implications of the study are also twofold. Firstly, the findings show that the effects of the antecedents of satisfaction can be more differentiated. Instead of assuming that all antecedents have a direct link to supplier satisfaction (Hüttinger et al., 2014), the antecedents are ordered into a causal hierarchical model. This model distinguishes between first- and second-tier factors, taking interdependencies between factors into account. Secondly, the findings support the hypothesis of a plentitude of scholars (Essig & Amann, 2009; Hüttinger et al., 2014; Pulles et al., 2016; Schiele et al., 2011) that a buyer's focus on improving supplier satisfaction can yield substantial benefits. This study is the first to show statistically that for both direct and indirect procurement, the buyers with highly satisfied suppliers receive better status and ultimately better treatment than their competitors. These findings highlight the importance of research in the field of supplier satisfaction and urge scholars to further improve the explanatory as well as predictive performance of satisfaction measures.

This study also has limitations. Factors external to the dyadic exchange relationship between buyer and supplier are not yet included in the model. Corresponding factors are market structure, organizational inter-dependencies and (technological) uncertainties and should be included in future research. Secondly, future research should assess the differences between direct and indirect materials in additional industries and search for potential product-related contingency factors, such as the phase within the product-life cycle in which a certain product falls. The impact of antecedents could vary depending on a combination of factors, such as product, supplier and environmental characteristics, which have not been addressed in this research. Finally, with only 9% response rate for direct procurement, this study might not be representative for direct procurement suppliers in the automotive sector. Therefore, this research tries to mitigate the effects of potential non-response bias by controlling for the days respondents needed to respond to the questionnaire. Still, the results are vulnerable to nonresponse bias concerning the variables perceived access to contacts and operational excellence. Accordingly, future studies should mitigate a non-response risk by having response rates that reflect at least the common rates of >20% in supply management research (Caniëls et al., 2013; Corsten et al., 2011).

In conclusion, as shown within this research, using a mixture of replication and extending previous research as well as applying advanced (prediction-oriented) methods can be very valuable for getting novel insights in a research field. Subsequently, other researchers should follow similar approaches, since in particular the combination of replication, explanatory modeling and prediction-orientated out-of-sample analyses allows a systematic comparison of different contexts and helps scholars to build more coherent research models. In particular the usage of the new prediction-oriented analyses techniques (i.e., PLSpredict and 10-fold cross

validation) helps us to identify valuable models for the application in the diverse contexts of both academics and practitioners.

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Appendix A. Questionnaire items for preferential treatment and profitability

Preferential treatment (Pulles et al., 2016; Schiele et al., 2011)
Our firm …
PT1 … allocates our best employees (e.g., most experienced, trained, intelligent) to the relationship with this customer.
PT2 … shares our best ideas (e.g., newest, most innovative) with this customer.
PT3 … allocates more financial resources (e.g., capital, cash) to the relationship with this customer.
PT4 … grants this customer the best utilization of our physical resources (e.g., equipment capacity, scarce materials).
PT5 … shares more of our capabilities (e.g., skills, know-how, expertise) with this customer.
Profitability (Hald et al., 2009; Ramsay & Wagner, 2009)
The relationship with this customer …
P1 … helps us to achieve good profits.
P2 … allows us to gain high margins.
P3 … has a positive influence on the profitability of our firm.

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