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STATED PREFERENCES FOR TRANSPORT AMONG INDUSTRIAL CLUSTER FIRMS

Gunther Maier*, Edward M. Bergman**

Department of City and Regional Development
Vienna University of Economics and Business Administration
Roßauer Lände 23
A-1090 Vienna, Austria

ABSTRACT

Stated preferences for – and contingent valuations of – various transportation options are by now well-established approaches to study firm logistics and freight movement choices. At the same time, there is a growing literature that connects intra-industry trade between regional production centres, plus greater industrial concentration and regional specialisation of centres, fuelled in part by less expensive and more efficient transport services. Finally, these increasingly specialised regional centres have acquired many of the key features described in the burgeoning industrial cluster or district literatures (Bergman and Feser, 1999). This paper reports on an ambitious effort to consider several of these individual points at various phases of a research project, one designed to estimate probable effects of proposed modal split centres and improved transportation services on the economic growth of key industrial clusters. It makes several novel points concerning modelling procedures and

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* email: gunther.maier@wu-wien.ac.at

** email: edward.m.bergman@wu-wien.ac.at

discusses the substantive findings from both a theoretical and policy perspective.

1. INTRODUCTION

This paper has its origins in a policy problem that requires analytic findings to support one or more transportation remedies. The problem concerns the role of Austrian surface transportation networks (road, rail, water) that serve the freight movement needs within the country and to neighbouring countries, particularly the EU-accession countries (see figure 1). Among the options under consideration are the establishment or upgrading of several modal split logistics centres where freight shipments are assembled, redistributed or transferred between modes, and forwarded to the final destination. Much of this is based on engineering options, but the underlying motivations of shippers, competing transport modes, and the long-run effects on the nation and its regions are economic in nature (see the IMONET WebPages at http://www.imonet.or.at/).

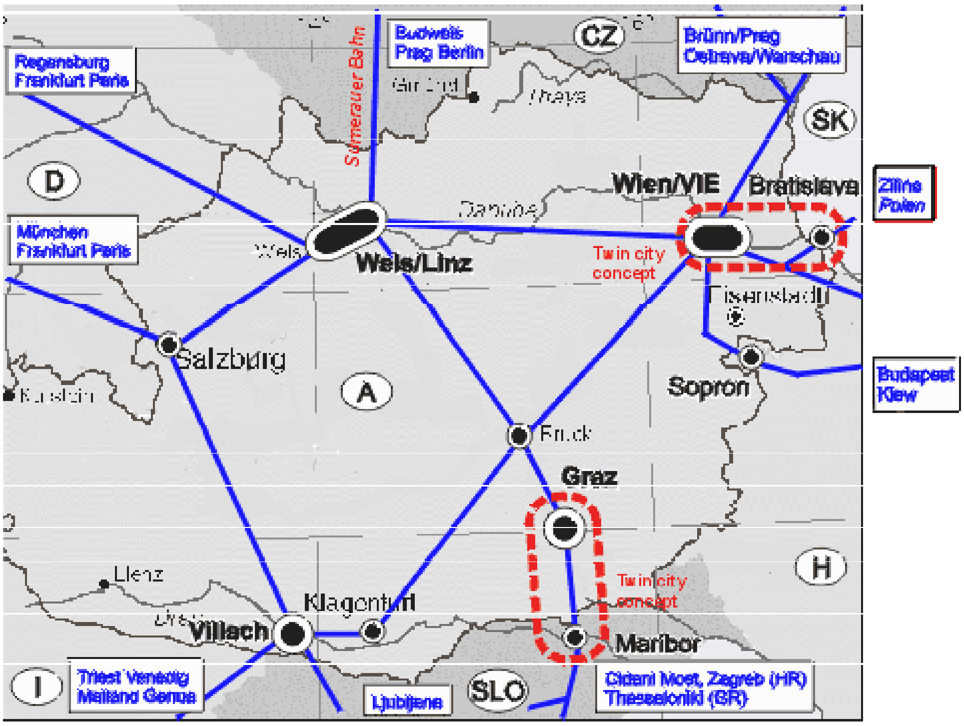
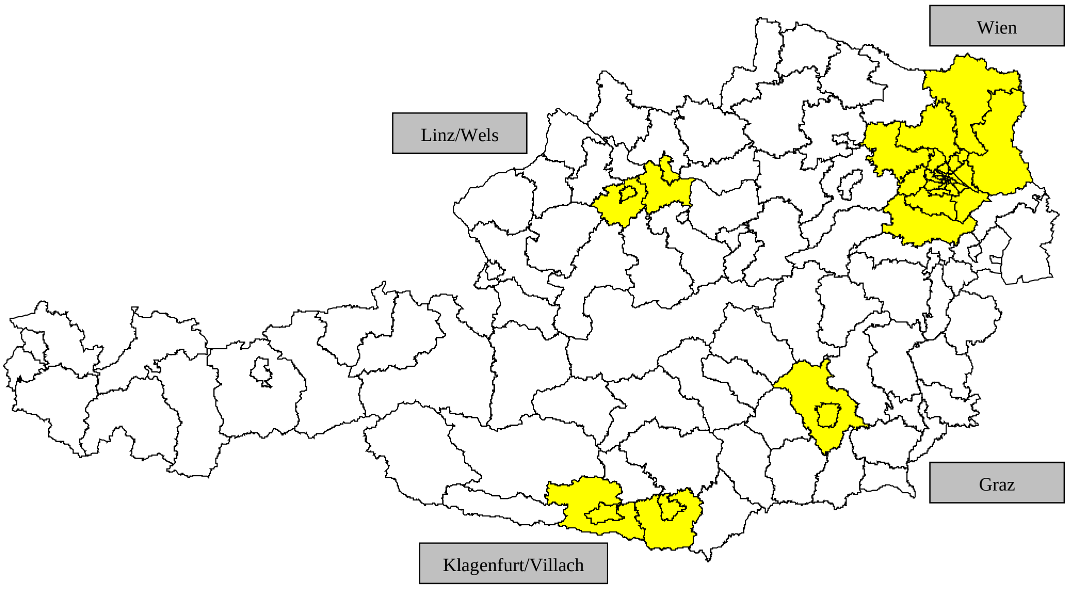


Figure 1: National and international linkages

To grasp this very large issue with minimal research resources, we elected to simplify the nature of the problem in two ways, first by focusing only on trade-driven transport between manufacturing industries, and second to consolidate all Austrian manufacturing industries into one of several industrial clusters, based on an exhaustive version of OECD value-chain definitions (Feser and Bergman, 2000). The latter simplification permits efficient sampling of firms by industrial classification that are known to engage in cross-shipping goods of related product or technology branches in manufacturing. Existing templates of value-chain clusters were adapted to Austrian industrial classifications, using established procedures and various concordance tables. Published industry figures were then mapped and the size and distribution of industrial cluster employment were attributed to specific regions. These distributions formed the basis for a stratified sample of Austrian firms by region and cluster, which were subsequently interviewed to elicit their stated preferences for various transportation options and service levels that support their ongoing logistics and trade.



Our results permit useful generalisations about firm's willingness to pay for certain transportation improvements that might result from the changed practices of transport providers or the establishment of efficient modal split logistics centres. The overwhelming consensus drawn from other stated-preference or transportation studies (e.g., Bolis, Maggi, 1999, Fowkes, et.al., 1991*)* also gain strength from our central findings *: reliability of service is of utmost importance to all regions and industrial clusters, and that use of rail to attain a range of desired transport objectives would require significant price reductions*. Other less obvious findings reveal key differences between Austria's various clusters and regions of potential theoretical interest and that can be used to fine-tune or shed more light on important policies.

2. REGIONAL CLUSTER CONCEPTS OF TRANSPORT LOGISTICS

Although the transport logistics problem was initially conceived by IMONET as an industrial and civil engineering issue at the national and international levels, our overall contribution to this research essentially draws upon regional economics for principal concepts . We first studied broad patterns across all the Austrian Laender as necessary background to our primary focus on the specific border regions most likely to host major transportation system improvements: Vienna (Slovakia/Hungary), Linz-Wels (Czech Republic/Germany), Graz (Slovenia/Hungary), and Villach-Klagenfurt (Slovenia/Italy). These specific regions and border corridors were given within the terms of our Interreg II-c Project (see the IMONET WebPages at http://www.imonet.or.at/), although it was our task to establish the analytic boundaries and provide the necessary background data from secondary sources.

We further translated the initial transport problem into one that permitted us to introduce theoretically and empirically useful degrees of regional complexity, which also helped reduce needless empirical detail by consolidating into logical groupings all regional firms and industries that ship goods and between which trade and transport naturally arise. The logic of consolidation is based upon existing analyses of input-out relationships between very detailed industries that trade routinely with one another within what OECD (1999) calls ‘value-chain clusters.’ Value-chain clusters are far more useful for our purposes than the type of clusters defined by other criteria (e.g., Porter, 2000 or Rosenfeld, 1997, primarily because value-chains represent inter-industry trade, while other cluster approaches rely upon criteria quite unrelated to trade, transportation or logistics. A considerable body of research has already analysed various dynamics and features of the industrial sectors associated with each of more than twenty possible value-chain clusters that arguably arise in all advanced market economies, the results of which are discussed in Bergman and Feser (1999).

Some value-chain clusters may consist of as few as 4 detailed industry components, while others may contain more than 100. Using international concordances and pre-tested procedures to estimate equivalent industries (Bergman and Lehner, 1998), all detailed Austrian industry employment groups were classified into one of seven non-exclusive value-chain clusters in the following relative proportions:

Figure 3: Clusters

CLUSTER	1991 MFG EMPLOY	CLUSTER MFG/ TOTAL MFG.
Metal Working	289,360	.40
Motor Vehicles	234,560	.32
Chemicals/Pharmaceuticals	187,300	.26
Electronic/Electrical	169,700	.23
Food	100,960	.14
Wood/Paper	100,400	.14
Construction Materials	24,200	.03

The seven clusters listed above sum to more than 100% of total 1991 employment because certain specific industries are members of *more than one cluster*, thanks to their broad inter-industry trading networks, which leads to multiple-counting if one simply totals nominal cluster employment levels.

The four largest clusters include industries that account for approximately 70% of net total manufacturing employment, while the remaining three account for about 30%. The smallest 3 clusters are natural resource-dependent and therefore mainly ship output to other downstream producers, while receiving few, if any, input shipments from other producers. These three are also less widely distributed among the regions under consideration for transportation corridor improvements, and they will face the stiffest competition once accession states are free to compete in markets for these goods, while the larger clusters have the greatest expansion potential. For many such reasons, relatively more attention was paid to the transportation needs of firms in the largest clusters.

With this basic information, it is possible to identify which of the study regions and transportation corridors have the highest relative concentrations (location quotients) in each cluster, thereby providing a framework for selecting a stratified sample of firms.[1] These

	Region Villach/Klagenfurt					Region Linz/Wels					Region Graz					Region Wien				
	employment			LQ		employment			LQ		employment			LQ		employment			LQ	
Cluster	**91**	**95**	**91-95 (%)**	**91**	**95**	**91**	**95**	**91-95 (%)**	**91**	**95**	**91**	**95**	**91-95 (%)**	**91**	**95**	**91**	**95**	**91-95 (%)**	**91**	**95**
motor vehicles	7418	5216	-29,7	1,19	0,92	20800	15548	-25,3	0,89	0,83	9494	12045	26,9	1,02	1,26	74171	53354	-28,1	1,32	1,20
chem/pharm	7581	5997	-20,9	1,53	1,38	21274	15358	-27,8	1,14	1,07	8659	6673	-22,9	1,17	0,91	50798	34292	-32,5	1,14	1,01
constr. mat	1361	1608	18,1	2,12	2,75	1548	1595	3,0	0,64	0,83	1083	1041	-3,9	1,13	1,06	3596	2802	-22,1	0,62	0,61
elektronics	6919	5952	-14,0	1,54	1,38	15566	11907	-23,5	0,92	0,83	7792	6354	-18,5	1,16	0,87	54010	50165	-7,1	1,33	1,48
food	[illegible]	[illegible]	[illegible]	0,90	0,80	[illegible]	6654	[illegible]	[illegible]	0,74	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	1,17	1,05
metal working	8263	5657	-31,5	1,08	0,83	41559	31687	-23,8	1,44	1,41	12911	13529	4,8	1,13	1,18	63254	44574	-29,5	0,92	0,84
wood/paper	[illegible]	[illegible]	-3,3	0,34	0,76	[illegible]	6216	8,5	0,57	0,66	4572	4045	-11,5	1,15	0,84	10033	8891	-11,4	0,42	0,40
manufact.	19517	18842	-3,5			73569	62224	-15,4			29107	31708	8,9			175616	147646	-15,9		

[1] Highly detailed regional- and cluster-specific descriptive analyses and mapping of 1991-1995 sectoral data is available in the final IMONET report submitted to Interreg II-c consortium sponsors.

results are shown in the following table (figure 4).

Using this basic information and that available from the master list of firms and establishments (number employees, age of firm, international exports, location, etc.) which served as our sampling frame, we sampled firms such that: a. regional concentrations of specific industries are represented, b. coverage of key sectors across the four main clusters is assured, c. firms with high percentages of regional employment are preferentially sampled, and d. all stratification factors receive adequate representation. It is vital that the sample be stratified by key factors that ensure the possibility of obtaining stated preferences for groups of firms vitally affected by various transportation proposals.

3. DATA COLLECTION

Interviews were held with the logistics officers of our sample of firms, following a thorough pre-test of all instruments and the consequent understanding of the respondent's perspective. The overall response rate was good, which resulted mainly from direct telephone contact with the officers and some explanation of our research. Some logistics officers resisted co-operating without knowing more about the purpose and detailed information to be collected, which necessitated pre-interview faxing of some phase1 questions to certain firms.

Phase 1 questions were printed as a typical interview form, on which either the respondent or interviewer entered typical information about the firm's basic shipping facts (products, destinations, typical modes, etc.). This phase took no more than 10-15 minutes and helped establish the rapport necessary to conduct the second phase (although in a few cases follow-up telephone calls were necessary to clarify the information supplied). The second – the conjoint analysis interview - consisted of a repeated set of choices recorded directly on the interviewers' portable computer, whose software presented a consistent, on-screen series of price-feature scenarios as alternatives to the baseline shipment facts provided by the respondent (described in more detail below).[2] Each *response* is taken as a separate

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[2] Data were collected by Vienna University of Economics and Business team members for the Vienna and Linz-Wels regions; data for the Graz and Villach-Klagenfurt regions were collected by the two other research groups, one an independent co-operating research group within the IMONET project and the other under contract control of the Vienna team. Most of the data for Vienna had been collected before that team briefed the Graz and Villach-Klagenfurt teams on how best to administer the computer scenario interviews (CSI). Thorough

observation at the analytic phase. The respondent's selections were automatically coded into the analytic categories used later in a series of maximum likelihood estimations.

4. CONJOINT ANALYSIS: STRUCTURE AND ESTIMATION

The conjoint alternative scenario approach is a well-established procedure for collecting stated preference information from respondents. In the context of freight transport the method has been used among others by Bates, 1988, Fowkes and Tweddle, 1997, Bolis and Maggi, 1999, Engel, 1996. The interview questions of this part of the interview were presented in a series of forms that the respondent "filled in." In every interview we tried to run through two mutually independent conjoint experiments, one for a typical transport relation on the input side, and one for a typical transport relation on the output side of the company. In a number of cases only one of the experiments could be completed.

Each repetition of the conjoint experiment started with a form (Figure 5) where the interview partner was asked to describe a typical transport relationship of the company in a number of dimensions. From these the basic analytic categories of the conjoint analysis were computed:

COST	of a typical shipment
TIME	required for delivery of shipment
RELIABILITY	in percentage point of on-time shipments
FREQUENCY	in hours between shipments
FLEXIBILITY	in minimal notice time (hours) to request shipment
MODE	transportation mode used

Additional transport characteristics of the respondent firm were recorded in the first step of the analysis. They are to be used for differentiating observations in later analyses.

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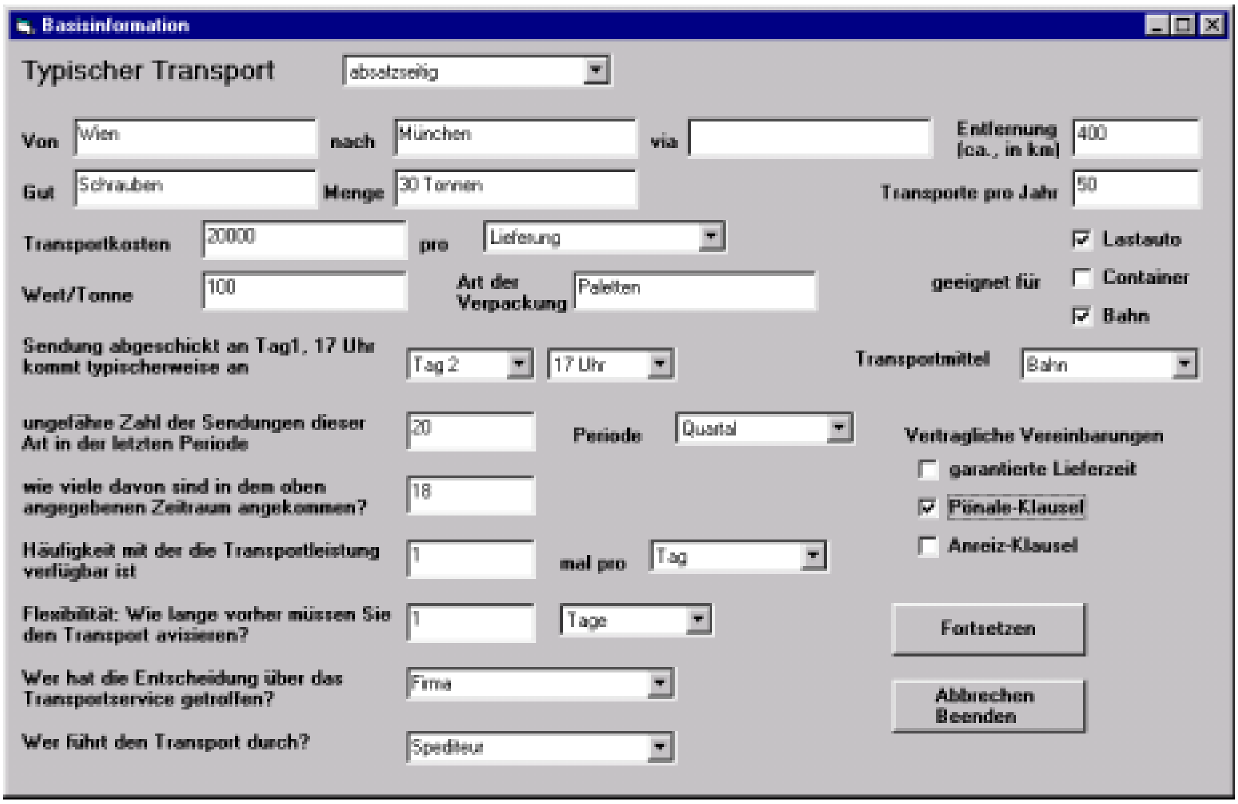
briefings of how best to consistently deploy our standardised data collection *instrument* permitted all teams to gather remarkably stable and useful information from firms in a variety of clusters from very different regions. In our project, all interviews were handled directly on the interviewer's portable computer, the computer program for which was written by Gunther Maier in Visual Basic.



In the second step, basic shipment information collected in the first round were used to generate a series of hypothetical alternatives to be evaluated by each respondent firm's logistics manager. In every repetition of the conjoint experiment the respondent was asked to compare his/her original transportation service (as reported in step 1) with 20 computer generated hypothetical alternatives, taken one at a time. The alternatives were described by the above mentioned six characteristics. For each interview, this procedure produced up to 40 binary comparisons between the original transportation service and a hypothetical alternative; 20 for the input side and 20 for the output side.

The characteristics of the hypothetical alternatives were generated from known characteristics of the firm's original transportation service. When generating the characteristics of the hypothetical alternatives we applied the following principles:

1. Only the first five of six characteristics shown above (German) can be described by a continuous variable. For those characteristics we used continuous variations.
2. For all the continuous characteristics there are clear hypotheses about the sign of their marginal utility[3]: COST < 0, TIME < 0, RELIABILITY > 0, FREQUENCY < 0,

[3] Take into account the definition of FREQUENCY and FLEXIBILITY given above.

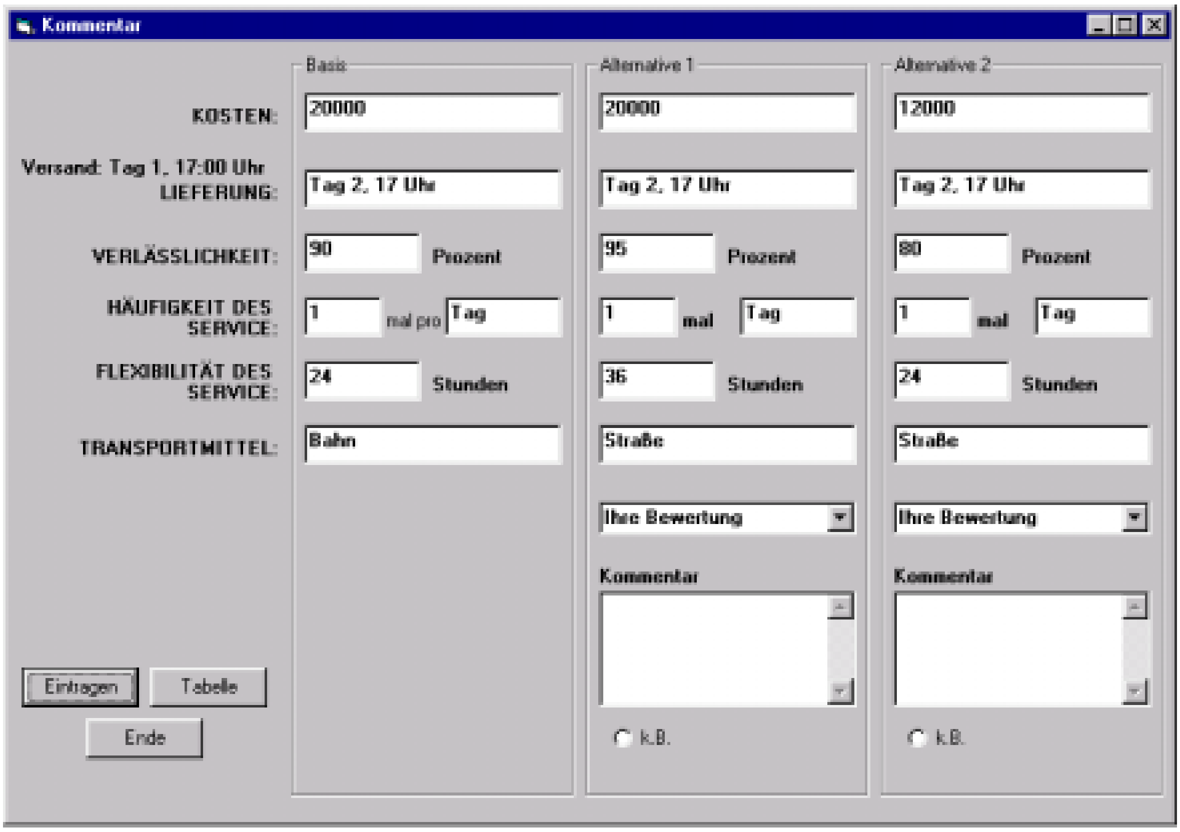
FLEXIBILITY < 0. Therefore, for each characteristic we know whether a higher value should in general be considered better or worse than a baseline value.

3. For each of the continuous characteristics we computed a higher and a lower value as compared to the value given by the respondent in step 1 of the analysis. In doing so, the computations had to be constrained to certain intervals:
   - COST, TIME, RELIABILITY, and FREQUENCY have to be non-negative,
   - RELIABILITY has to fall between 0% and 100%.

   We used exponential and logistic functions to ensure values that are consistent with these constraints. Because of this
   1. The actual variations of the characteristics depend upon the original value, and
   2. When the original value reported by the interview partner in step 1 of the analysis is at one of the extremes (e.g., 100% reliability or a value of 0 for flexibility), one of the variations is degenerate and coincides with the original value.
4. In generating the hypothetical alternatives we substituted only two of the original continuous variables; one with the better value, one with the worse. The other three continuous variables were always kept at the value of the original alternative. This way we ensured that – with the exception of the few cases where there were degenerate variations – none of the two alternatives in an evaluation was apriore superior to the other.
5. MODE is a discrete variable that can take on various values. By far the most important shipment modes presently in use are ROAD (85%) and RAIL (11%). In scenario simulation experiments, the MODE variable was changed only when the original value was ROAD or RAIL. In the remaining 4 percent of interviews, the variable MODE remained unchanged from its original value.

When we apply these principles, we can generate 40 alternatives[4] for each original transportation service. In the case of degenerate variations or when the variable MODE remains unchanged, some of these alternatives the characteristics may be identical. In each conjoint experiment we generated the full set of 40 alternatives and then selected 20 of them randomly to be used in the second step of the experiment.

[4] We can combine the 5 continuous variables in 10 different pairs where the first variable has a better characteristic, the second variable a worse one. Reversing this relationship yields another 10 pairs. For each of these 20 possible alternatives the mode can be switched, thus doubling the number of potential alternatives.



The computer form used in the second step of the experiment is shown in Figure 6. The questionnaire form always repeated the respondent's original transportation service and presented a hypothetical alternative generated by the CSI. The respondent then had to decide whether a hypothetical alternative was much better, better, slightly better, slightly worse, worse or much worse than the original service. Even though responses were graded by relative intensity, they were reduced to two: better OR worse. Further, the response categories did not permit respondents to be indifferent between the original and its alternative transportation solution, in order to force a decision, although they were permitted to refuse to answer if a decision was impossible. In the subsequent estimation process, a refused response is considered equivalent to indifference (missing value); we are confident that this overall approach yields more, reliable observations available for use in estimation procedures.

When estimating the model, positive and negative evaluations of a hypothetical alternative are equivalent to its acceptance or rejection, which yields a set of binary decisions (stay with the original transportation service – switch to the hypothetical service) that can be used for estimating a discrete choice model.

Based on random utility theory the decision of the interview partners can be described in the following form. Suppose the value of hypothetical alternative i to interview partner n can be characterised by the following random utility function:

$$V_{in} = \beta_1 X_{1i} + \beta_2 X_{2i} + ... + \varepsilon_{in}$$

V_{in} characterizes the value alternative i has to interview partner n, X_1, X_2, ... represent the characteristics of this alternative, β_1, β_2, ... are unknown parameters, and ε represents an unobservable random influence in the respondent's evaluation of this alternative. A similar random utility function is assumed for the original transportation service:

$$V_{0n} = \alpha + \beta_1 X_{10} + \beta_2 X_{20} + ... + \tau_n + \varepsilon_{0n}$$

Since alternative i is hypothetical and alternative 0 real and well known to the interview partner, we can expect that the respondents will tend to prefer alternative 0 over the hypothetical one. In order to capture this persistence we have added an additional parameter α that acts as an alternative specific constant. However, not all respondents may excert the same level of persistence. Their random fluctuations around α is captured by the additional random component τ_n in the above equation. Note that the function for the original alternative has two random components, ε and τ. The term τ characterizes that ranom influence that is specific to the interview partner and does not change over the alternatives, ε characterizes those random influences that vary with the alternatives and interview partners.

The basic assumption of discrete choice theory is that a respondent will select the alternative that yields the highest level of random utility. So, alternative i will be preferred over alternative 0 only when

$$V_i > V_0$$

When we substitute the above equations for V_i and V_0, we see that alternative i will be preferred over alternative 0 only when

$$-\alpha + \beta_1(X_{1i} - X_{10}) + \beta_2(X_{2i} - X_{20}) + ... > \varepsilon_{in} - \varepsilon_{0n} + \tau_n$$

This equation shows two things:

1. It is the difference in the characteristics of the alternatives that is of relevance for the decision.
2. The right hand side of the equation contains not just the difference in the alternative specific random components, but also the individual specific random component τ.

The latter point is of particular importance for the estimation procedure since it implies that our observations in the estimation are not independent. This violates one of the statistical assumptions of standard discrete choice models.

This problem also occurs in panel data analysis, where the same respondent is typically observed more than once. Two possible solutions have been developed for this problem that are known as (1) fixed effect model, and (2) random effect model (Hsiao, 1986). The fixed effect model treats τ_n as an unknown constant that is shifted over to the left hand side and is estimated as an individual-specific/alternative-specific constant. This way the fixed effect model restores the statistical properties of the standard discrete choice model. In the random effect model τ_n is specified as a random variable with its own probability distribution. The parameters of this mixing function are estimated in the estimation procedure. Because of the complex statistical structure of the model, standard discrete choice models cannot be used in this case.

Clearly, the fixed effect model is much easier to estimate. The drawback of the model, however, is that because there is usually only a limited number of repeated observations, the fixed effect parameters cannot be estimated consistently. Moreover, because of the nonlinearity of the model, the inconsistency of the fixed effect parameters is transferred over to the structural parameters making them inconsistent as well. As compared to typical panel data models with 2-4 panel waves, however, our conjoint experiment generates a fairly large number of repeated observations. Therefore, we are confident that the statistical problems of the fixed effect model are marginal relative to its computational advantages.

Depending on the distributional assumptions about the error term ε, we will get different discrete choice models. In the case of just two alternatives, these models are very similar. We assume ε to be extreme-value distributed, an assumption that leads to the Logit-model (Ben-Akiva and Lerman, 1985, Maier and Weiss, 1990). It implies the following function for the probability that alternative i is preferred over the original alternative:

$$P_i = 1 / \{1 + \exp[\alpha + \tau_n + \beta_1(X_{10} - X_{1i}) + \beta_2(X_{20} - X_{2i}) + ...]\}$$

The final model consists of the following variables:

- The generic variables COST, TIME, RELIABILITY, FREQUENCY, and FLEXIBILITY as described above.
- An alternative specific constant α.
- A respondent specific alternative specific constant τ_n for every respondent except the first one. The parameter of the first respondent must be set to zero exogenously in order to avoid linear dependence with the alternative specific constant.
- A dummy variable RAILMODE that is one when the respective alternative uses the rail-mode, and zero otherwise,
- A dummy variable RAILACCESS that is one when RAILMODE is one and the company reports that it has direct rail access, zero otherwise. This variable takes into account the availability of rail infrastructure.

6. ESTIMATION RESULTS

In this section we will report the results of our estimation. We will concentrate on two technical and substantive aspects of the estimation results, namely (1) the role of the repeated observations (as discussed above), and (2) the question of whether respondents from different regions or industrial clusters tend to evaluate transport options differently.

Both aspects can be analysed by estimating different versions of the model and comparing their likelihood by use of a likelihood ratio test. In order to test the regional and cluster differences, we need to expand the list of variables that we have described above. For all these variables, with the exception of the respondent specific alternative specific constants, we can define region-specific as well as cluster-specific versions. These variables are equal to the respective base variable when the observation belongs to the specific cluster or region, and zero otherwise. In principle, this yields a full set of generic variables, alternative specific constant, and RAILMODE and RAILACCESS dummies for every region as well as every cluster. In order to avoid perfect collinearity, however, some variables have to be omitted. We omit:

- The respondent-specific/alternative-specific constant for the first respondent, else the respondent-specific/alternative-specific constants would sum to the alternative specific constant.
- All the variables for the Vienna region, else the region-specific vectors would add up to the respective vector of the base variable.
- All the variables for the automotive sector for the same reason.
- The region- and cluster-specific/alternative-specific constants because of their perfect collinearity with the respective subset of respondent-specific alternative specific constants.

Figure 7 shows the results for four different versions of the model. The versions differ by the eligible groups of variables that are included or excluded. Model 1 includes all eligible variables: base variables, cluster variables, and regional variables. Model 2 excludes the regional variables from the estimation, model 3 excludes cluster variables but includes regional variables, and model 4 excludes both categories and consists of only the base variables. In all four models we have used the full set of respondent specific alternative specific constants in order to correct for the potential bias that we have discussed above. Because of their large number and their irrelevance to the interpretation of the model, they will go unreported here.

		Model 1	Model 2	Model 3	Model 4
Base variables	CONST	**2.2769943**	**2.1367087**	**2.2202435**	**2.1990035**
	COST	**-0.0009430**	**-0.0002684**	**-0.0005963**	**-0.0002640**
	TIME	-0.0014729	*-0.0202792*	-0.0204311	**-0.0308703**
	RELIAB	**0.2824902**	**0.2097852**	**0.3837230**	**0.1957094**
	FREQ	*-0.1819077*	*-0.1703324*	-0.0547530	**-0.0296777**
	FLEX	**-0.1496032**	**-0.0149742**	**-0.1332479**	**-0.0174050**
	RAILMODE	-0.2872587	**-0.7315773**	*-0.7387797*	**-0.7041280**
	RAILACCESS	1.3757610	1.8471456	-0.1926517	*0.4982767*
C	COST_M	-0.0000201	-0.0000273	---	---
	TIME_M	**-0.0655835**	**-0.0698437**	---	---
	RELIAB_M	-0.0144389	-0.0002785	---	---
	FREQ_M	0.0693203	0.0593561	---	---
	FLEX_M	**-0.0369495**	**-0.0353473**	---	---
	RAILMODE_M	-0.1238962	-0.1119611	---	---
	RAILACCESS_M	-1.9829334	-0.0701242	---	---

	COST_C	0.0000477	-0.0000410	---	---
	TIME_C	-0.0134962	-0.0028027	---	---
	RELIAB_C	0.0815036	-0.0413539	---	---
	FREQ_C	0.0840948	*0.1474428*	---	---
	FLEX_C	0.0048205	0.0084048	---	---
	RAILMODE_C	-0.2673178	0.1081218	---	---
	RAILACCESS_C	-2.8088809	-1.5908480	---	---
	COST_E	**0.0004705**	0.0000322	---	---
	TIME_E	-0.0160838	-0.0063596	---	---
	RELIAB_E	0.1342692	0.0487853	---	---
	FREQ_E	0.1383766	**0.1929581**	---	---
	FLEX_E	0.0238213	*-0.0356342*	---	---
	RAILMODE_E	-0.6760025	-0.0791631	---	---
	RAILACCESS_E	-2.0079687	-1.8547731	---	---
Regional variables	COST_L	**0.0006320**	---	**0.0003525**	---
	TIME_L	-0.0080009	---	-0.0094774	---
	RELIAB_L	-0.0886157	---	*-0.1675848*	---
	FREQ_L	*0.0732393*	---	0.0277848	---
	FLEX_L	**0.1624602**	---	**0.1269687**	---
	RAILMODE_L	0.4794538	---	0.8222480	---
	RAILACCESS_L	1.4090634	---	0.4502994	---
	COST_G	**0.0006899**	---	**0.0003611**	---
	TIME_G	-0.0204827	---	-0.0122527	---
	RELIAB_G	-0.0607003	---	**-0.1858523**	---
	FREQ_G	-0.0172845	---	*-0.0840588*	---
	FLEX_G	**0.1356775**	---	**0.1107943**	---
	RAILMODE_G	-0.4918752	---	-0.0939075	---
	RAILACCESS_G	na	Na	na	na
	COST_K	*0.0002908*	---	**0.0003500**	---
	TIME_K	-0.0128573	---	-0.0066979	---
	RELIAB_K	-0.2755526	---	**-0.2860781**	---
	FREQ_K	*0.0891417*	---	0.0571682	---
	FLEX_K	**0.1412563**	---	**0.1315794**	---
	RAILMODE_K	-0.0202888	---	0.0092075	---
	RAILACCESS_K	1.6828856	---	0.6225604	---
	max. Likelihood	-1158.13838	-1205.18873	-1194.02847	-1257.12897

Figure 7: Estimation results[5]

5 Regions and clusters are indicated by the character added to the name of the base variable. The correspondence is as follows: M – machinery, metalwork, C – chemicals, pharmaceuticals, E – electronic, electrical; L – Linz, G – Graz, K – Klagenfurt, Villach. Parameters significant at the 5% level are printed in *italics*, parameters significant at the 1% level in **bold**.

Although the statistical significance of the parameters is somewhat disturbed by the correlation between the cluster and regional variables on the one hand and their respective base variable on the other, the estimation results are quite good. Even in model 1 most of the base variables have significant coefficients, all of them with the expected signs. At this step, however, we don't want to discuss the meaning of specific parameter values, but want instead to compare the four models to detect the effects of variable groupings. Models 2 – 4 are constrained versions of model 1. In each of them a group of parameters that were estimated in model 1 is explicitly constrained to zero. This is *equivalent* to the hypothesis that the respective group of variables does not contribute to understanding the model; or, more specifically, that the valuations of our respondents do not differ by region and/or cluster to which their firms belong.

Because of this structure of the models, we can test the statistical significance of the respective hypotheses by use of a likelihood-ratio test. The last row in figure 7 gives the logarithm of the likelihood. The test statistic for the likelihood ratio test is simply twice the difference between the log-likelihood of the unconstrained and that of the constrained model. This test statistic is chi-square distributed with the degrees of freedom being equal to the number of constrained parameters.

	Reg	Clust	None
Reg/clust	71.78 (21)	94.10 (20)	197.98 (41)
Reg			126.20 (20)
Clust			103.88 (21)

Figure 8: Likelihood ratio tests (row and column headings show which group of variables is included in the estimation)

Figure 8 shows these likelihood ration test statistics. The degrees of freedom are given in parentheses. The row and column headings show which groups of variables have been constrained to zero. All test statistics in figure 8 clearly exceed their respective critical value at the 1%-level. So, we have to reject all hypotheses. Obviously, the evaluation differs by region and cluster of the respondent. In order to avoid biasing the estimations, we have to allow for both regional and cluster specific variations of the parameter values.

A full set of respondent-specific/alternative-specific variables is used in the estimation in order to correct for the potential bias resulting from repeated observations. Since this correction uses up a large number of degrees of freedom, it is advisable to test the hypothesis that the respondent specific alternative specific constants do not contribute to the explanatory power of the model. This test will also tell us whether the results of other conjoint experiments that do not employ such a correction are likely to be biased.

In order to perform this test, we estimate model 1 of figure 7, but exclude all respondent specific alternative specific constants, and calculate the likelihood-ratio statistic as before. The value of the test statistic is 242.09, which is almost twice the critical value for 96 degrees of freedom at the 1%-level. So, we can conclude that

- the correction for repeated observations is important for the overall quality of the model, and
- estimations that do not address this problem adequately most likely yield biased parameter estimates.

Having clarified which is the appropriate model structure –i.e., that which includes cluster and regional variables and respondent-specific/alternative-specific constants – let us turn now to the interpretation of the model results. For this step, we reestimate the model, eliminating step by step all insignificant structural variables. The results of this procedure can be found in figure 9. Since the alternative-specific constant is influenced by the respondent-specific/ alternative-specific constant and therefore differs from one respondent to the other, we have excluded it from the table.

	BASE	LINZ	GRAZ	KLAGENF.	METAL	CHEM/ PHARM.	ELECTR.
COST	-0.0008910	0.0005744	0.0006375	0.0003003	0	0	0.0004059
TIME	-0.0246546	0	0	0	-0.0600569	0	0
RELIAB	0.2105991	0	0	-0.2490916	0	0.120722	0.1932181
FREQ	-0.1198865	0.0898314	0	0.1113132	0	0	0.0560972
FLEX	-0.1320076	0.1415139	0.1186848	0.1287929	-0.0372093	0	0
RAILMODE	0	0	-0.8678235	0	0	0	-0.9475656
RAILACCESS	0	0	0	0	0	0	0

Figure 9: Estimation results

Because of the specification requirements of the model, the baseline estimation (column BASE) actually represents the automotive cluster in the Vienna region. The values in the other columns show the statistically significant deviations from that corresponding baseline value. Therefore, the parameter estimates for a specific cluster in a specific region need to be calculated from figure 9. The parameter for flexibility (FLEX) for the metal working cluster in Linz, for example, is the sum of the base figure, the figure for the metal working cluster, and the figure for region Linz (i.e., -0.0277), although not all combinations were sampled and therefore cannot be “summed.” (see Figure 11 note below).

General Model Approximation

The structure of our estimated model shows directly what variables are valued differently by respondents from certain clusters and/or regions. However, we cannot easily derive any insight into the general meaning of parameter values for the combined regions and clusters. The general structure is hidden somewhat behind the detailed answers of the model. In order to approximate that general structure, we have used the estimation results of figure 9, calculated the parameter values for every observation in the dataset, and computed the mean values. This gives a weighted average of the parameter values of the various clusters and regions with the number of observations being the weights.

The result of this step is shown in figure 10. The first column – mean coefficients – shows the weighted means, the second column – compensating costs – shows the same information transferred into monetary terms. This second column gives the amount of money that the respondents in average would be willing to pay – in the case of a positive value – or would require as compensation – in the case of a negative value – for a one unit increase in the respective variable.

	mean coeff.	comp. cost
COST	-0,00034767	--
TIME	-0,04660246	-134,04413
RELIAB	0,22224781	639,25845
FREQ	-0,07712218	-221,82899
FLEX	-0,03928936	-113,00923
RAILMODE	-0,65434820	-1882,12259
RAILACCESS	0	0

Figure 10: mean coefficients and compensating cost

All parameters have the expected signs. Higher costs (COST) and higher travel times (TIME) make a proposed transport service less attractive. Higher reliability (RELIAB) makes it more attractive. Since frequency (FREQ) and flexibility (FLEX) are measured in terms of hours between services or hours until the service becomes available, the negative signs of these parameters imply that higher frequency and more flexibility of the service is valued positively. The variable RAILMODE measures an autonomous preference toward the rail mode. In the final model this variable yielded a significant parameter only for one region and one cluster. However, in more restricted model versions (e.g., model 4 in figure 8) this parameter consistently turned out to be significantly negative. This indicates a penalty toward rail in the general evaluation of transport services, a penalty which becomes distributed in the service coefficients of cluster- and region-specific alternatives posed in more detailed models. Other things equal, logistics managers tend to disfavour rail service (or service qualities associated with rail) over other modes of freight transport. However, the variable RAILACCESS never produces a significant parameter value. This variable measures the convenience effects of rail-mode for those companies that have direct rail access. The fact that this variable drops from the estimation shows that RAILMODE truly measures a rail penalty, not the absence of infrastructure access.

Looking at the second column of Figure 10, we see that reliability (RELIAB) obviously is the most important characteristic in logistic manager's evaluation of transportation services. A one-percentage point increase in reliability is valued to be equivalent to a cost reduction of ATS 639,-- per shipment. By comparison, a one-hour reduction in travel time (TIME), time between shipments (FREQ) or notification time (FLEX) is valued between ATS 113,-- and ATS 222,-- per shipment. When we compute compensating costs, it turns out that the penalty for rail transport is quite substantial. An average logistics manager in Austria's main or, equally logically, the *reduction* in shipment prices a manager would demand *if* rail service were substituted. Many and sometimes quite vivid reasons were offered during interviews justifying their distaste for rail service, and some reasons overlapped other CSI dimensions (reliability, frequency, flexibility). There is clearly room for improvement in rail service offered to cluster firms, but there are no doubt limits to what is economically feasible for improving rail services built over time for an evolving industrial base that may bear only passing resemblance to Austria's principal industrial clusters.

Regional and Cluster-Specific Findings

Although almost all regions and clusters showed a significant rail penalty when we first estimated the model separately for every cluster and region (Maier, Bergman, 2000), the results in figure 9 indicate that this penalty is most pronounced in the Graz region and in the electrical/electronics cluster. For both, the rail penalty is considerably higher than the average number indicates. These results make good sense: among our set of regions, Graz is known to be the region worst-connected to the rail system; moreover, according to our respondent interviews, the electrical/electronics cluster in Austria ships components that are difficult to handle and very sensitive to outside influences. Many respondents from this cluster claimed their products require special attention when transported that they cannot get using rail mode.

Figure 9 breaks down the general results that we have discussed above by cluster and region. It is interesting to note that transport cost (COST) and flexibility (FLEX) are valued differently between all regions, but not between all clusters. This indicates that these variables are related to the availability and quality of infrastructure that differ by region, but not so much to the companies' typical needs that may differ by cluster. Travel time (TIME), on the other hand, is valued almost the same by respondents from all regions and clusters. Only the machinery/metal work cluster considers travel time significantly more important than the rest of the economy.

It seems from the results in figure 9 that the strong positive influence of reliability (RELIAB) is more than offset by the large negative coefficient of RELIAB in the region of Klagenfurt/Villach. However, since companies sampled from this region belong either to the chemical/pharmaceutical cluster or to the electrical/electronics cluster, the computed parameter for reliability becomes negative for none of the companies in our dataset. Therefore, the dominant positive role of reliability in selection of transport service is not weakened by this one negative parameter value.

To see the cost effects for all sampled combinations of region- and cluster-specific groupings, we have converted parameter to compensating cost figures in Figure 11, using methods similar to those used to prepare Figure 10. Beginning with rail-mode, the average shipment from sampled electrical-electronic cluster firms would have to be reduced in price by 2725.5

ATS to compensate for loss of perceived rail service levels, and a similar price reduction of 2496.1 ATS would be required by the average firm from Graz, including all its clusters. No other direct rail-mode effects were detected for other clusters or regions.

Clusters→ Regions↓	MOTOR VEHICLE	CHEMICALS-PHARMA.	ELECTRICAL-ELECTRONIC*	MACHINE-METALWORK
VIENNA	TI=-<u>70.9</u> RL=<u>605.7</u> FQ= -344.8 FX= **-373.9↑**	TI=-<u>70.9</u> RL=<u>605.7</u> FQ= **-2.4↓** FX= -373.9	TI=-<u>70.9</u> RL=**1161.5↑** FQ= -181.8 FX= -373.9	UNSAMPLED COMBINATION
GRAZ**	TI=-<u>70.9</u> RL=<u>605.7</u> FQ= -344.8 FX= -32.5	TI=-<u>70.9</u> RL=<u>605.7</u> FQ= -2.4 FX= -32.5	UNSAMPLED COMBINATION	TI=-<u>70.9</u> RL=433.0 FQ= -344.8 FX= -32.5
KLAGENFURT	UNSAMPLED COMBINATION	TI=-<u>70.9</u> RL=110.7 FQ= -24.7 FX= **-3.5↓**	TI=-<u>70.9</u> RL=**81.9↓** FQ= **-483.2↑** FX= -3.5	UNSAMPLED COMBINATION
LINZ-WELS	UNSAMPLED COMBINATION	TI=-<u>70.9</u> RL=<u>605.7</u> FQ= -344.8 FX= -373.9	UNSAMPLED COMBINATION	TI=-<u>70.9</u> RL=86.3 FQ= -86.5 FX= -33.1

*Average rail-mode <u>avoidance payment</u> by ***all*** Electrical/Electronic firms= *-2725.5 ATS*

Average rail-mode <u>avoidance payment</u> by ***all* Graz firms= *-2496.1 ATS*

Figure 11: Compensating Costs of Service Quality Alternatives by Region and Cluster

There were consistently stable service-level results across certain combinations (see <u>underlined</u> values). For example, the average firm in every regional cluster valued an hour of reduced shipment time by about 71 ATS, while half of all sampled combinations would pay the same (605.7ATS/pp) to obtain a percentage point increase in reliability. However, electric-electronic cluster firms in Vienna would pay nearly double (1161.5 ATS/pp) for improved reliability, while firms from this cluster in Klagenfurt would pay barely more than a ninth (81.9 ATS/pp). Extreme compensating costs values (↑↓) for each service feature are identified in **bold figures**.

In terms of overall satisfaction with available transportation services, the machine-metal working cluster firms in Linz-Wels are most satisfied/least will to pay for improvements, while electrical-electronic cluster firms in Vienna are least satisfied/most willing to pay for improvements. Interregional contrasts of service satisfaction are also a more precise way of describing the discrepancy in rail-mode avoidance payments discussed above*: Linz-Wels is the only region* wholly unaffected by either the blanket rail-mode avoidance payment that affects all Graz and all electrical-electronic firms (Klagenfurt and Vienna only). This further reinforces our earlier policy speculations (Maier and Bergman, 2000) about the relative adequacy and suitability of transportation infrastructure that favours the Linz-Wels region, particularly its metalworking and machinery cluster. Although it did not occur to us until the data were evaluated carefully from both perspectives, this finding should surprise no one: Linz-Wels is the region positioned closest to Austria's historically strongest trading partner, Germany. It also benefited from heavy industrial investment during the short period of national socialism, and Linz-Wels is highly concentrated in the industrial cluster most closely associated with the country's initial period of industrialisation and rail expansion. These significant historical factors may suggest a fairly strong case of regional/industrial cluster path dependence in rail transport that has become less functional in other dynamic post-1989 regions and industrial clusters.

6. SUMMARY

The analysis in this paper, which extended work reported in an earlier version of this paper (Maier, Bergman, 2000), shows that the valuation placed on alternative transport services by logistics managers of Austrian companies differs significantly by both their regional and their industry-cluster affiliation. Despite certain important critical variations, the study also shows strong and consistent influence of certain characteristics on the decision process. Most notably reliability of transport service is the dominant factor. Improvements in reliability seem to be of critical strategic importance for any supplier of transport services, because logistics managers are in average willing to pay a cost increase of ATS 639,-- (EURO 46.46) for an increase in reliability by one percentage point. Our estimation also shows a considerable reluctance by logistics managers to ship their products by rail. Everything else equal, rail in Austria would need to be ATS 1882,-- (EURO 136.78) cheaper per shipment for the average firm (and much more for Graz or for electric-electronic cluster firms) than a competitor who uses road transport.

On a technical side, our model also shows that in a conjoint experiment with repeated experiments per respondent it is important to take into account the statistical complications that are the price for this fairly easy way to generate large amounts of data. Applying a fixed-effect-model, we find that the correction contributes significantly to the statistical quality of the model, thus removing bias from the structural variables. This result indicates that the results of applications of this technique that simply ignore this problem should be viewed sceptically.

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