Is There Any Interaction Effect Between Intention and Perceived Behavioral Control?

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Many models in social psychology, which have been developed to explain behavior, postulate interaction effects between explanatory latent variables. In the last years, there have been many new developments for estimating interactions between latent variables in structural equation modeling. However, there have been very few applications with real data from theory-driven studies. This paper provides an empirical test with real data from an ongoing research project about travel mode choice in Frankfurt, using the theory of planned behavior. We apply three statistical approaches for the estimation of interaction effects between the latent variables perceived behavioral control (PBC) and intention for predicting travel mode choice (behavior): latent variable scores, maximum likelihood and robust maximum likelihood. We compare the strengths and weaknesses of the approaches from an applied point of view. In a meta-analytic review we summarize the results of 14 articles, which estimated the interaction between intention and PBC for predicting behavior, and discuss the problems associated with such a meta-analysis.

Keywords: Interaction effects; Structural Equation Modeling; latent variable scores; maximum likelihood; meta-analysis; theory of planned behavior; robust maximum likelihood.

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Many models in social psychology, which have been developed to explain behavior, postulate interaction effects between explanatory latent variables (e.g. Ajzen & Fishbein, 1980; Ajzen, 1991; Triandis, 1980). In the last years, there have been many new developments for estimating interactions between latent variables in structural equation modeling (Arminger & Muthen, 1998; Bagozzi, Baumgartner & Yi, 1992; Baumgartner & Baggozzi, 1995; Bollen, 1995; Bollen & Paxton, 1998; Busemeyer & Jones, 1993; Jaccard & Wan, 1995, 1996; Jöreskog, 1998; Jöreskog & Yang, 1996; Kenny & Judd, 1984; Klein & Moosbrugger, 2000; Klein, Moosbrugger, Schermelleh-Engel & Frank, 1997; Lee & Zhu, 2000; Li Fuzhong, Harmer, Duncan, Duncan, Acock & Boles, 1998; Marcoulides & Schumacker, 2001; Moosbrugger, Schermelleh-Engel & Klein, 1997; Ping, 1996; Reinecke, 2002; Reinecke, Schmidt & Ajzen, 1996; Schermelleh-Engel, Klein & Moosbrugger, 1998; Schumacker & Marcoulides, 1998; Wall & Amemiya, 2000; Yang-Jonsson, 1997; Yang-Wallentin & Jöreskog, 2001; Zhu & Lee, 1999). In the last years, there have been many new developments for estimating interactions between latent variables in structural equation modeling. Many of these studies investigated interaction effects by means of Monte Carlo methods. However, there have been only few applications with real data from theory-driven studies (Yang-Wallentin, Schmidt & Bamberg, 2001). So from a methodological point of view it would be very helpful to apply valid and reliable statistical tools on real data for the estimation of such interaction effects. When there are nonlinear relationships between latent variables, the general linear structural equation model (Jöreskog, 1973) does not hold, as pointed out by Hoogland and Boomsma (1998). It is indeed not possible to transform latent variables to make nonlinear relationships such as quadratic or interaction terms approximately linear, as can be done with observed variables.

For nonlinear structural equation models with product terms the pioneering work of Kenny and Judd (1984) is of special interest. They suggested using the product of the indicators of latent variables to control for random measurement error (Reinecke, 2002). Baumgartner’s and Baggozzi’s (1995) simulation results show that maximum likelihood (ML) and weighted least squares (WLS) performed well with respect to model estimation, but the chi square statistics and standard errors based on normal distribution theory may not be trustworthy. WLS estimators are most appropriate where the sample size is large enough. Yang-Jonsson (1997) compared simulations using ML and WLS estimation. They conclude that sample size greater than 400 is not a serious problem for the ML estimators although inference statistics are underestimated and the chi squares reject the model too often. With WLS the statistical assumptions are better fulfilled and
chi squared values have smaller values indicating a better model fit. Moulder and Algina (2002) suggest that two-stage least squares (TSLS) and Ping’s (1996, 1998) procedure are more likely to result with biased estimates of the interaction term than ML, whereas ML tests with corrected standard errors had convergence problems and were too conservative. Schumacker (2002) presents two approaches to latent variable interaction modeling. In the first procedure, the interaction is defined by multiplying pairs of observed variables (the ML Jöreskog-Yang approach), and in the second the latent variables scores are multiplied. Parameter estimations were similar, but standard errors were different. Future research should clarify the nature of the differences in the standard errors in these two approaches.

As Reinecke (2002) states, results often base on a limited number of cases (many times less than 500 cases) or on simulations rather than on real data (see for example Baumgartner & Baggozzi, 1995; Yang-Jonsson 1997). In our study we will try to overcome this limitation by using real data with considerably more cases.

From a meta-analytical point of view it is confusing. As Moulder and Algina (2002) state, several studies have been conducted on methods for testing and estimating latent variable interactions. However, these methods have often provided results for a single method and, therefore, did not allow for a general comparison of the available methods. When we decide which estimation methods to apply, we have to answer two questions:

a) Which estimation methods we choose and why?

b) Which one is the best out of them?

This paper provides a meta-analytic review of studies, which tested the intention × PBC interaction in the theory of planned behavior, and an empirical test of the interaction with real data from an ongoing research project about travel mode choice in Frankfurt, using the theory of planned behavior (Ajzen 1985, 1988, 1991).

1) In a meta-analytic review after the theory section, we summarize the results of 14 articles, which estimated this interaction, and discuss the problems associated with such a meta-analysis.

2) In the empirical test, we apply three statistical approaches for the estimation of interaction effects between the latent variables perceived behavioral control (PBC) and intention for predicting travel mode choice (behavior). The estimation methods are latent variable scores (LVS), maximum likelihood (ML) and robust maximum likelihood (RML). For example, we do not bring Klein’s method (Klein & Moos-
brugger, 2000; Klein, Moosbrugger, Schermelleh-Engel & Frank, 1997) although it has very good estimation properties especially for small samples. A simulation study is needed to compare this method with LVS, as they are both useful for small samples. TSLS and WLS are not tested here, because they have been studies before (see Yang-Wallentin, Schmidt & Bamberg, 2001). On the other hand, LVS, ML and RML are used for the following reasons:

- LVS is new and has been rarely empirically tested before. It is easy to implement and is suitable for a preliminary test for the interaction.
- ML is known to be a robust estimation method (Jöreskog, 1998; Yang-Jonsson, 1997; Yang-Wallentin & Jöreskog, 2001). Although ML requires the multinormal distribution, which we don't have because of the use of product variables, it still deserves to be considered according to simulation studies (Yang-Jonsson, 1997).
- RML is used to produce the correct standard errors and \( \chi^2 \) under non-normality (Browne, 1984; Satorra, 1993).
- ML and RML are complicated to implement, but they give parameter estimates and overall model fit simultaneously.

In contrast to most papers on this topic, we do not test the interaction between the constructs belief \( \times \) expectancies from the theory of planned behavior, but the interaction between the constructs intention and PBC for predicting behavior. We compare the strengths and weaknesses of the three approaches from an applied point of view. We do not provide mathematical documentation of the three methods, because we are more interested in their implementation. Therefore, we provide the input files for each method. Finally, we give a recommendation which estimation method to use to test interaction effects.

**Theory**

The Theory of Reasoned Action (TRA) (Ajzen & Fishbein, 1980), respectively the Theory of Planned Behavior (Ajzen, 1991), are not only among the most intensively empirically tested social psychological action theories (e.g. Armitage & Conner, 2001; Conner & Armitage, 1998; Eagly & Chaiken, 1993; Van den Putte, 1991), but they have also been applied successfully to the explanation of environmentally relevant behaviors (Allen, Davis & Soskin, 1993; Bagozzi & Dabholkar, 1994; Goldenhar & Connell, 1992-1993; Jones, 1990). Very briefly, the TPB, which is an extension of the TRA, postulates that people in a decision situation consider the likely consequences of available alterna-
tives (so-called behavioral beliefs); they weigh the normative expectations of important reference individuals or groups (normative beliefs); and they consider required resources and potential impediments or obstacles (control beliefs). These considerations or beliefs result, respectively, in the formation of attitudes towards the behavior of interest, subjective norms with respect to the behavior and PBC. It is assumed that people form behavioral intentions based on their attitudes, subjective norms, and perceptions of behavioral control, and that these intentions, together with behavioral control, are the immediate determinants of behavior. Figure 1 shows a graphical representation of the TPB.

![Figure 1. The Theory of Planned Behavior (TPB)](image)

Intention is assumed to capture the individual motivational factors, which influence behavior. It is an indicator of how much an individual is willing to try and how much energy he is willing to invest in order to perform a behavior. Generally speaking, the higher the intention the higher the chance a behavior will be performed.

It should be mentioned however, that intention determines behavior only if the person can decide at free will whether to perform or not to perform the behavior, i.e. whether the behavior is under volitional control. Whereas some behaviors may meet this requirement, they may depend on the availability of opportunities and resources ("resources" is the word usually used in economic theory). Such resources are for example time and money in neoclassical economics (e.g. Becker, 1965) or skill and cooperation of
others (Ajzen, 1985). Together, these factors represent individual’s control over the behavior. The importance of actual behavioral control is self-evident: the resources and opportunities available to a person determine by some extent his behavioral performance. Of greater psychological or sociological interest are however not the actual behavioral controls or restrictions, but the perceived ones and their effect on intention and performed behavior. The Theory of Planned Behavior, as described in Figure 1, places the PBC in a more general framework, where simultaneously also the effects of norms and attitudes towards the behavior are considered.

The three constructs PBC, attitude towards the behavior and perceived social norms in the TPB are believed to determine intention directly. PBC and intention are believed to determine behavior.

The joint determination of intention is quite straightforward: the basic idea is that when individuals form intentions, they take into account their attitude towards that behavior, the social norms prevailing concerning the behavior and their PBC. An individual will not form an intention to do something, unless he thinks there is some chance of converting this intention into behavior given the behavioral control. Thus, one could formulate three alternative models; one in which there could be only a direct effect of intention and PBC on behavior; a second one containing only an interaction between intention × PBC; finally, a model with the two additive effects and the interaction effect (see Equation 1).

The interaction effect may be understood in two ways: a psychological and a non-psychological one. First, we may believe that an individual will increase his intention to perform a behavior when his PBC is higher. Indeed, an individual will be more motivated and try to perform a behavior harder than another individual with the same intention but with more perceived limitations on the behavioral performance. Ajzen (1991) calls this the interaction hypothesis of intention × PBC on behavior (see Figure 2).³

³ In future research, one should investigate whether this postulated interaction effect holds for both dimensions of PBC, perceived control and self-efficacy, which were described in Ajzen, 2002.
The second explanation for the role played by PBC in jointly determining behavior is less psychological in nature. In this sense, an individual with an intention will fail to perform the behavior, if his actual behavioral controls are lower. Here we are not speaking about a higher or a lower motivation to perform a behavior, but rather on the ability to perform it. When the ability to perform the behavior is lower simply because of lower control on the behavior, the intention to perform it will be indeed lower.

A review of twelve studies (Ajzen, 1991) confirms the hypothesis of Ajzen that in the case of behaviors, which are not under total volitional control, PBC supported a good prediction of intention and behavior. However, the empirical findings concerning the “interaction-hypothesis” of intention and behavioral control on behavior are inconsistent. Ajzen reports the findings of seven studies, which test this hypothesis. Of these studies, only one (Schifter & Ajzen, 1985) obtains a marginally significant interaction between intention and PBC. In the following section, we report an extended meta-analysis of studies, which explored empirically the interaction term PBC × Intention in the theory of planned behavior.

**Meta-analysis of studies exploring whether there is a significant interaction term between PBC and Intention in the TPB**

When deciding to include a meta-analysis in our report, we were confronted with the question of which kind of meta-analysis to include. One can think of at least two alternative sorts of meta-analyses. The first is to report a summary of methodological studies, which tried to develop techniques or test interaction effects in general (e.g. Hoogland & Boomsma, 1998). In recent years, many researchers have developed meth-
ods of estimation, and some even compared the strengths and weaknesses of different techniques. We mentioned some of them in our introduction. Such a meta-analysis would be beyond the scope of this paper. Another alternative, which is more substantive in nature, would be to include only studies, which tried to test the interaction term between PBC and Intention in the theory of planned behavior. In this paper, we are going to extend a report of Armitage and Conner (2001), which concentrated in the meta-analysis on substantive results of the interaction effects of the TPB. We would relate to the results from a methodological point of view in order to learn about the state of the art of the study of this interaction.

Such a meta-analysis necessarily depends on the state of the art of the existing methods to test such an interaction. Jöreskog (1998) points out, that if the interaction variable is latent, the factor scores approach or the two stage least squares (TSLS) method are probably the most reasonable to use. A full information approach according to Jöreskog should be used only if one has a very large sample and one is capable of understanding how to specify the nonlinear constraints implied by the model. At that point in time (1998), this was the recommendation. However, as methods to test interaction effects rapidly develop, could it be that reasonable methods to test it might as well change? For instance, as mentioned before, Klein, Moosbrugger, Schermelleh-Engel and Frank (1997) and Moosbrugger, Schermelleh-Engel and Klein (1997) developed a new approach (LMS) for estimating interaction effects. According to their work, their method is better for small samples than all other methods. However, a systematic comparison of their approach with the other approaches just mentioned by using Monte Carlo simulations is missing.

Concerning the role of measurement error in a meta-analysis, Hunter and Schmidt (1990, p. 539) suggest that:

“It is our belief that many real methodological problems are captured by the rubrics “errors of measurement” and “range variations”. Error of measurement in particular is universal, although some studies may have much poorer measurements than others”. Thus, one of the main differences between Armitage and Conner’s (2001) meta-analysis and ours is that we try to control for studies, which applied corrections for attenuation. As Scherpenzeel and Saris (1997) and Saris (2001) demonstrated, different sorts of control for measurement errors influence the results. This must be taken into account in a meta-analysis. However, we cannot do it because we have no information about the measurement errors in those studies.
Armitage and Conner (2001) located several studies that tested the intention × PBC hypothesis. We base on their analysis and extend it. In Table 1, one can find a summary of the results of this meta-analysis.

**Table 1**

*Meta Analyses of the Interactive Effect of Intention and PBC on Behavior* (see note)

<table>
<thead>
<tr>
<th>Study Number</th>
<th>Study</th>
<th>Number</th>
<th>Intention × PBC&lt;sup&gt;a,b&lt;/sup&gt;</th>
<th>Estimation method used</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Beck and Ajzen (1991)</td>
<td>34 (additional 46 in control group)</td>
<td>n.s.</td>
<td>Ordinary Least Squares (OLS)</td>
</tr>
<tr>
<td>2</td>
<td>De Vellis, Blalock, and Sandler (1990)</td>
<td>70</td>
<td>n.s.</td>
<td>OLS</td>
</tr>
<tr>
<td>3</td>
<td>Doll and Ajzen (1992)</td>
<td>75</td>
<td>n.s.</td>
<td>OLS</td>
</tr>
<tr>
<td>4</td>
<td>Dzewaltowski, Noble, and Shaw (1990)</td>
<td>254</td>
<td>n.s.</td>
<td>OLS</td>
</tr>
<tr>
<td>5</td>
<td>East (1993)</td>
<td>One study-75, Another study-145</td>
<td>n.s.</td>
<td>OLS</td>
</tr>
<tr>
<td>6</td>
<td>Kimiecik (1992)</td>
<td>332</td>
<td>b=0.24</td>
<td>OLS</td>
</tr>
<tr>
<td>7</td>
<td>Morojele and Stephenson (1994)</td>
<td>1&lt;sup&gt;st&lt;/sup&gt; sample-87, 2&lt;sup&gt;nd&lt;/sup&gt; –61 (sub sample)</td>
<td>n.s. in 1&lt;sup&gt;st&lt;/sup&gt; sample, beta=-0.72 in 2&lt;sup&gt;nd&lt;/sup&gt;.</td>
<td>OLS</td>
</tr>
<tr>
<td>8</td>
<td>Prislin and Kovrlija (1992)</td>
<td>53</td>
<td>Beta= 0.593</td>
<td>OLS</td>
</tr>
<tr>
<td>9</td>
<td>Schifter and Ajzen (1985)</td>
<td>83</td>
<td>b= 0.2</td>
<td>OLS</td>
</tr>
<tr>
<td>10</td>
<td>Terry and O’illery (1995)</td>
<td>146</td>
<td>c)</td>
<td>SEM-ML</td>
</tr>
<tr>
<td>11</td>
<td>Theodorakis (1994)</td>
<td>395 (females only)</td>
<td>n.s.</td>
<td>OLS</td>
</tr>
<tr>
<td>12</td>
<td>White, Terry, and Hogg (1994)</td>
<td>211</td>
<td>Beta=0.17 (in one test), n.s. in another.</td>
<td>OLS</td>
</tr>
<tr>
<td>13</td>
<td>Yang-Wallentin, Schmidt, and Bamberg (2001)</td>
<td>1,115</td>
<td>d)</td>
<td>Multi-group analysis in SEM (ML); WLS; TSLS.</td>
</tr>
<tr>
<td>14</td>
<td>Reinecke, Schmidt, and Ajzen (1996)</td>
<td>1,500</td>
<td>e)</td>
<td>Multi-group analysis in SEM (ML).</td>
</tr>
</tbody>
</table>

*Note.* Parts of the table are from an unpublished table of Armitage and Conner (2001).

<sup>a</sup>Studies involving regression analyses have been done for the full TPB model. Some analyses report the beta coefficient, some the b coefficient, some the gamma coefficient (between the interaction term and behavior). More details are given for the significant interaction terms. <sup>b</sup>Where a coefficient b or beta are reported, they were found significant in that study at least at the 5% level; n.s.- not significant; significance is in the 5% level or higher. In some studies the b coefficient was reported whereas in others the beta. <sup>c</sup>In a multi-group analysis estimates for the path linking intention to actual behavior were considerably higher (beta=0.65) in the high PBC group than in the low one (beta=0.18). <sup>d</sup>In a multi-group analysis some estimates for the path linking intention to behavior were considerably different in the high
PBC group compared to the low one in different estimation methods. The path (b) for bus, bike and car was .093, 1.5 and .24 in the high PBC group compared to .25, .9 and .24 in the low one, respectively with WLS estimation (for car the difference was n.s.). With TSLS estimation, the unstandardized interaction term on behavior was -.076, -.061 and .015 for bus, bike and car respectively (for car n.s.). With ML estimation, the unstandardized interaction term on behavior was -.089, -.157 and -.001 for bus, bike and car respectively (for car n.s.). In a multi-group analysis estimates for the path linking PBC to behavior were considerably higher in the high intention group (beta=.29) than in the lower one (-.33). Additionally, estimates for the path linking intention to actual behavior were considerably higher (0.55) in the high PBC group than in the low one (beta=0.18).

Indeed, the estimation techniques presented in Table 1 differ substantially. One of the most frequent arguments against meta-analyses is that they mix apples and oranges (Hunter & Schmidt, 1990). That is, meta-analyses combine studies that are so different that they are not comparable (see also Lipsey & Wilson, 2001). In our case, we compare tests results of the same interaction effect in the same model. However, samples range in size, data collection techniques differ, and variables differ. Moreover, the estimation technique changes from study to study, and it is often recognized as inappropriate. As mentioned, according to Hoogland and Boomsma (1998), measurement errors should be taken into account. Therefore, according to this recommendation and to Jöreskog (1998) structural equation modeling is the preferred method for the estimation of the interaction effect. Also Hunter and Schmidt (1990) present in detail the need for corrections for attenuation. Nevertheless, according to Hunter and Schmidt (1990), eliminating from a meta-analysis studies that are perceived as having methodological inadequacies is not a desirable practice. They contend that methodological inadequacies do not necessarily produce biased results. Therefore, we include all studies in our comparison.

However, we report the results in the voting method (details about this and other methods of meta-analyzing are presented in Hunter & Schmidt, 1990). This method counts the number of studies, which belong to one of the categories: (1) significant and positive effect; (2) significant and negative effect; (3) not significant. We have four main reasons for this: (1) Many of the samples are not random samples; (2) most studies do not control for random and nonrandom measurement errors (see Hunter & Schmidt, 1990, p. 102 for correcting the variance for sampling error); (3) estimation methods used are not always the optimal ones and often apply ordinary least squares (OLS) regression analyses; (4) the content of the constructs differs. This might lead to opposite signs of the interaction effects, and thus to the impossibility of computing means of correlation coefficients. What makes our job easier is the fact that there is a relatively small number of studies to meta-analyze.
As one can see, eight of the studies found no significant interaction effect between PBC and intention in some or in all of their tests. They applied OLS techniques to test the interaction hypothesis. Eight studies found in some or in all of their tests significant interaction effects (two of them found a non-significant interaction in one test). Three of them used different estimation methods with structural equation modeling. These studies exclude our analysis, which is following this section. The interaction term in these studies ranged between –0.72 and 0.25. Seven studies found a positive interaction effect, and two of them found also a negative one. In addition, one study found only a negative interaction effect. A possible reason for finding a negative interaction effect in contrast to the theory is multicollinearity. In the study relating to travel mode choice (Yang-Wallentin, Schmidt & Bamberg, 2001), part of the interactions between PBC and intention (for bike and for bus use) were negative and significant. A negative sign of the interaction might be affected by the content of the constructs as well. Thus, not controlling for estimation method, we conclude that about half of the studies found no interaction effect between intention and PBC in the theory of planned behavior. In three of them, the interaction effect was found to be negative. However, when taking into consideration only studies, which correct for attenuation, all three studies show a significant interaction effect. Two of them indicate positive and negative interaction effects, and the third only a positive one (our following analysis finds a positive interaction effect, too, and controls for measurement errors). A positive interaction effect would demonstrate that an increasing PBC intensifies the effect of intention on behavior.

According to Armitage and Conner (2001), Ajzen (1991, p. 188) suggests, that failure to find an effect may be attributable to the fact that linear models provide good accounts of psychological data even when interaction effects are known to be present. Additionally, if PBC is unrelated to actual control, the extent to which PBC would moderate the relation between intention and behavior is unclear. Another reason, is that especially in regression models, computation of product terms may have led to severe multicollinearity, which leads to insignificant results and changes in the coefficient signs. Finally, according to Ajzen, strong interactions are likely only if the measures of PBC and Intention both cover the full range of the response scales. Restriction of range to either the positive or negative side of the scale will tend to attenuate observed interaction effects. In the following sections, we would report a test of the interaction effect between intention and PBC on data of travel mode choice with three different techniques, latent variable scores (LVS), maximum likelihood (ML) and robust ML (RML).
Propositions

As a result of the scope of our task and the methodological orientation of the paper, we do not test all propositions of the theory of planned behavior. This includes all the interactions of the beliefs and the interaction between intention and PBC. Such an inclusive simultaneous analysis has never been done (for a test only of belief products, see Reinecke, 2002; Yang-Jonsson, 1997). We concentrate on the effects of intention and PBC on behavior, especially if there is any interaction between the effects of these two constructs on behavior. The analyzed behavior is the percentage of public transport use in Frankfurt during one day reported by our participants. This percentage is computed from the total of car and public transport use (thus, behavior constitutes a continuous variable).

Travel mode choice is an interesting behavior, due to the fact that the impact of intention and PBC is expected to be different on behavior when different travel modes are used. The main difference between public transport and the car is that public transportation is in principal provided to the total population, and its availability depends on its quality, frequency, location of bus or train stops and destination. These are objective characteristics of the behavioral control of using public transport. On the other hand, a car is a private means of transportation, which is not available to everyone in Germany. Whereas the main obstacle of using the car is its availability, the main obstacle of using the public transport is its quality of service.

From the Theory of Planned Behavior we can derive the following propositions concerning the effects of intention and PBC on behavior:

Propositions:

1) We expect to find a positive effect of PBC on behavior.

2) We expect to find a positive effect of intention on behavior.

Concerning the interaction between intention and PBC, we expect the following:

3) We expect to find a positive and significant interaction effect between PBC and Intention on behavior.

In Figure 3 we illustrate the propositions we are testing (see the results section).
Study design and measurement

Sample

The data were collected as the first wave of a panel study, which should evaluate travel mode choice in Frankfurt\(^4\). 5,000 randomly selected inhabitants of the city of Frankfurt received a questionnaire by mail at the end of September 2001. A reminder was posted on the 12\(^{th}\) of October 2001. In November 2001 there was an additional reminder. 1,334 of the questionnaires were sent back by the 17\(^{th}\) of January 2002 (and another 4 by April 2002) (a response rate of 27\%). The analysis is based on responses of 1,328 inhabitants, who had reported at least one trip on the selected day using the car, public transport or a bike. 47\% were men, and the average age was 44.3 years (with a standard deviation of 15.7). After eliminating the missing values (list-wise) in the analyzed variables, the actual sample size reduced to 912.

Measurements

In the study, all constructs of the theory of planned behavior were measured. However, these constructs do not refer to using public transport, car, bike or walking. Rather, these constructs refer to the motivation of individuals to change from using the car to using public transport. Nevertheless, we believe these constructs serve us well, because our reference group is the group of individuals using either a car or public transport. Persons using other means of transportation are not included in our analyses.

The following description includes measurement instruments for the constructs used in the analysis.

*Perceived Behavioral Control (PBC)*\(^5\) - direct measures:

- It would be possible-impossible for me to use public transport rather than the car for everyday purposes here in Frankfurt in the next weeks (x1).
- I am sure that I can use public transport rather than the car for everyday purposes here in Frankfurt in the next weeks. Sure-not sure (x2).

\(^4\) Supported by the DFG (German Science Foundation), project number SCHM658/7-1.

\(^5\) Following the differentiation of Ajzen (2002) between perceived control and self-efficacy, according to our interpretation, our items correspond to the self-efficacy definition.
The response range was a five-step bipolar scale from 5 (possible, true) to 1 (impossible, false)\(^6\).

**Intention (Int) -direct measures:**

- My intention to use public transport rather than the car for everyday purposes here in Frankfurt in the next weeks is big-small (x3).
- How probable is it, that I use public transport rather than the car for everyday purposes here in Frankfurt in the next weeks? Probable-improbable (x4).
- I intend to use public transport rather than the car for everyday purposes here in Frankfurt in the next weeks (probable-improbable) (x5).

The response range was a five-step bipolar scale from 5 (big, probable) to 1 (small, improbable).

**Behavior (Be)- one direct measure:**

The actual behavior, which was travel mode choice, was measured by the use of a standardized protocol of all routes a person had traveled on one day in a chronological order (Spiegel-Documentation, 1993). From these travels we compute the percentage of public transport use from the total use of public transport and car on the reported day to all reported destinations (pt\%)..

As one can see in Table 2, the three intention indicators are highly correlated with one another and with the behavioral variables. The two PBC indicators are highly correlated with one another, with the three intention indicators as well as with the behavioral variables. Since all the variables are interval, we do not get into the discussion on the problems that come out in the analysis of interaction effects when some of the variables are not interval (see Van den Putte & Hoogstraten, 1997). In the next section we proceed with the analysis.

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\(^6\) This is only partly in line with Allison’s (1977) suggestion, that both components of the interaction must have a ratio scale. Whereas all the values of the indicators of PBC and Intention are positive, the lowest value of each of them is 1 and not zero.
Table 2:

Means, Standard Deviations and Correlations for the Observed Variables

<table>
<thead>
<tr>
<th></th>
<th>x1</th>
<th>x2</th>
<th>x3</th>
<th>x4</th>
<th>x5</th>
<th>pt%</th>
</tr>
</thead>
<tbody>
<tr>
<td>x1</td>
<td>1.000</td>
<td>.738**</td>
<td>.660**</td>
<td>.711**</td>
<td>.659**</td>
<td>.407**</td>
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<tr>
<td>x2</td>
<td>1.000</td>
<td>.767**</td>
<td>.808**</td>
<td>.785**</td>
<td>.479**</td>
<td></td>
</tr>
<tr>
<td>x3</td>
<td>1.000</td>
<td>.852**</td>
<td>.828**</td>
<td>.525**</td>
<td></td>
<td></td>
</tr>
<tr>
<td>x4</td>
<td>1.000</td>
<td>.869**</td>
<td>.520**</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>x5</td>
<td>1.000</td>
<td>.557**</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>pt%</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>1.000</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th></th>
<th>M</th>
<th>SD</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>3.8</td>
<td>1.37</td>
</tr>
<tr>
<td></td>
<td>3.51</td>
<td>1.54</td>
</tr>
<tr>
<td></td>
<td>3.24</td>
<td>1.58</td>
</tr>
<tr>
<td></td>
<td>3.36</td>
<td>1.59</td>
</tr>
<tr>
<td></td>
<td>3.19</td>
<td>1.58</td>
</tr>
<tr>
<td></td>
<td>.2671</td>
<td>.4128</td>
</tr>
</tbody>
</table>

**p < .01 (two tail).**

Data Analysis

In this section, we analyze the data set from the described study of travel mode choice in Frankfurt. We start with defining the variables in the analysis denoting:

\[ \eta_1 = Be \]
\[ \xi_1 = PBC \]
\[ \xi_2 = Int \]

The estimated structural model with the interaction is:

\[
Be = \alpha + \gamma_1 PBC + \gamma_2 Int + \gamma_3 Int PBC + \zeta, \quad (1)
\]

We checked for correlations also for the subgroup of people who use public transport in a lower frequency than “always” (which was the highest frequency for public transportation use in the questionnaire), and received the same pattern of correlations. The factor loadings with a value of 1.000 are fixed values to set the scales for the latent constructs.
Equation (1) contains in addition to the direct effects of Int and PBC on Be (behavior) an interaction effect of Int and PBC on Be (IntPBC). \( \gamma_1, \gamma_2, \) and \( \gamma_3 \) are the corresponding regression coefficients, and \( \zeta \) is the error term of Be. In Figure 3, the error terms are noted as e1-e12.

There are three indicators x3, x4 and x5 for Int, two indicators x1 and x2 for PBC, and one indicator for Be (pt%), thus Be is measured by a continuous observed variable. The indicators for the product latent variable IntPBC are formulated by using cross products of three observed Intention items, x3, x4 and x5 and the two PBC items, x1 and x2. There are six possible choices and all of them have been used as indicators of IntPbc, as presented in Figure 3\(^8\), x1x3, x1x4, x1x5, x2x3, x2x4, and x2x5.

\[ \begin{align*}
  &e1 \\
  &e2 \\
  &e3 \\
  &e4 \\
  &e5 \\
  &e6 \\
  &e7 \\
  &e8 \\
  &e9 \\
  &e10 \\
  &e11 \\
  &e12
\end{align*} \]

\[ \begin{align*}
  &1 \\
  &1 \\
  &1 \\
  &1 \\
  &1 \\
  &1 \\
  &1 \\
  &1 \\
  &1 \\
  &1 \\
  &1 \\
  &1
\end{align*} \]

\[ \begin{align*}
  &x1 \\
  &x2 \\
  &x1x3 \\
  &x1x4 \\
  &x1x5 \\
  &x2x3 \\
  &x2x4 \\
  &x2x5 \\
  &x3 \\
  &x4 \\
  &x5 \\
  &pt\%
\end{align*} \]

\[ \begin{align*}
  &INTPBC \\
  &Be \\
  &INT \\
  &PBC
\end{align*} \]

*Figure 3. Path diagram of the model with six product variables.*

\(^8\) The notation in Figure 3 is an AMOS 4.0 notation (Arbuckle, 1999).
According to Ping (1998), the number of product indicators can become large. Specifying many product variables might lead to problems in execution times, convergence and to problems in the solutions. However, for the sake of content validity it could be argued that it is needed to use all product variables when it is not clear which products can be dropped. As this was our case, we used all of them. In the case of specifying and testing the interactions in the Kenny-Judd model, the selection can be done in a theory-driven way (see Reinecke, 2002). In the following sub-sections, we will describe our three estimation methods for the interaction effect, and the results for each.

**Testing the measurement model**

To begin with we test the measurement model by specifying a confirmatory factor analysis model with three correlated factors.

The model is fitted by WLS. The estimates of the factor loadings and the measurement error variances are shown in Table 3.

Table 3  
*Parameter Estimates for Measurement Model*

<table>
<thead>
<tr>
<th>Measure</th>
<th>Be</th>
<th>PBC</th>
<th>Int</th>
<th>Error variance</th>
</tr>
</thead>
<tbody>
<tr>
<td>Pt%</td>
<td>1.00</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>X1</td>
<td>-</td>
<td>1.00</td>
<td>-</td>
<td>0.80</td>
</tr>
<tr>
<td>X2</td>
<td>-</td>
<td>1.31</td>
<td>-</td>
<td>0.34</td>
</tr>
<tr>
<td>X3</td>
<td>-</td>
<td>-</td>
<td>1.00</td>
<td>0.48</td>
</tr>
<tr>
<td>X4</td>
<td>-</td>
<td>-</td>
<td>1.07</td>
<td>0.22</td>
</tr>
<tr>
<td>X5</td>
<td>-</td>
<td>-</td>
<td>1.03</td>
<td>0.35</td>
</tr>
</tbody>
</table>

**Estimating the interaction effect by means of latent variable scores (LVS).**

The latent variable scores are computed by an extension of a formula given by Anderson and Rubin (1956). These scores are unbiased estimates of the latent variables and their sample covariance matrix is equal to the estimated covariance matrix of the reference variable scores. Estimating the interaction effect by means of latent variable scores is new and simple (Jöreskog 2000; Jöreskog, Sörbom, du Toit & du Toit, 2000,
It is a two-step procedure, and the command files are presented in the body of the text and not in the appendix, since this method has not been tested before.

In the first step, one estimates the scores of the latent variables so that the scores satisfy the same relationships as the latent variables themselves. In this step, we first convert the RAW data file to a PSF (PRELIS SYSTEM FILE) running the following PRELIS file of commands:

```
Computing PSF file from rawdata
DA NI = 6
LA
BEHAV1 INT1 INT2 INT3 PBC1 PBC2
RA = LIMIT1.RAW
CO ALL
OU MA = CM RA = LIMIT1.PSF
```

These commands will also produce a DSF file (Data System File). To obtain the latent variables scores for Be, PBC and Int one uses the DSF and the following SIMPLIS file of commands:

```
Computing Latent Variable Scores
System file from file PSF1.dsf
Latent Variables Behav Int Pbc
Relationships:
  INT1 = 1 * Int
  INT2 - INT3 = Int
  PBC1 = 1 * Pbc
  PBC2 = Pbc
PSFfile LIMIT1.PSF
End of Problem
```

The latent scores for Be, PBC and Int will be listed in the LIMIT1.PSF.

In the second step one estimates the interaction effect using the latent variable scores obtained in the first step. Using LISREL 8.30 or a later version (Jöreskog, Sörbom, du Toit & du Toit, 2000) and the following PRELIS input file this is easily done.
Estimating the Nonlinear Equation

\[ SY = LIMIT1.PSF \]
\[ NE \ Int Pbc = Int * Pbc \]
\[ CO ALL \]
\[ RG BEHAV1 ON \ Int Pbc IntPbc \]
\[ OU \]

As earlier mentioned, the latent variable scores method is new and no evaluations of it have been documented. A systematic study of this method is a task for future research. The results of our travel mode choice data are shown in Table 4.

Table 4

*Estimates of \( \gamma \) with LVS*

<table>
<thead>
<tr>
<th></th>
<th>( \gamma_1 )</th>
<th>( \gamma_2 )</th>
<th>( \gamma_3 )</th>
</tr>
</thead>
<tbody>
<tr>
<td>Estimate</td>
<td>0.075</td>
<td>0.113</td>
<td>0.069</td>
</tr>
<tr>
<td>Standard error</td>
<td>0.025</td>
<td>0.020</td>
<td>0.009</td>
</tr>
<tr>
<td>T-values</td>
<td>2.972</td>
<td>5.712</td>
<td>7.342</td>
</tr>
</tbody>
</table>

In Table 4 one can see that the interaction effect between PBC and intention on Behavior is significant as well as the additive effects of Intention and PBC. The effect of PBC seems to be the weakest (in terms of significance). The effects of intention and of the interaction seem to be much stronger, and the interaction effect has the most significant impact on behavior.

**Maximum Likelihood Method (ML)**

ML is a full information method. It was proposed by Jöreskog and Yang (1996) and investigated by Yang-Jonsson (1997). In a full information method one simultaneously fits the moment matrix implied by the model to the corresponding sample moment matrix by minimizing a fit function with respect to all parameters (see Yang-Wallentin, Schmidt & Bamberg, 2001). In principal, full information methods provide the best parameter estimates and standard errors. However, ML is based on the assumption that the observed variables have a multinormal distribution. This assumption does not hold because of the use of product variables. According to Yang-Jonsson (1997), ML performs often well for sample sizes over 400, but it computes asymptotic standard errors...
and Chi-squares incorrectly. In the following section, we use the robust maximum likelihood method (RML) to correct the standard errors and the Chi-square. The implementation of ML is shown in Appendix B. The results are shown in Table 5.

Table 5

*Estimates of $\gamma$ with ML*

<table>
<thead>
<tr>
<th></th>
<th>$\gamma_1$</th>
<th>$\gamma_2$</th>
<th>$\gamma_3$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Estimates</td>
<td>0.11</td>
<td>0.08</td>
<td>0.07</td>
</tr>
<tr>
<td>Standard errors</td>
<td>0.06</td>
<td>0.04</td>
<td>0.01</td>
</tr>
<tr>
<td>T-values</td>
<td>1.88</td>
<td>1.76</td>
<td>8.15</td>
</tr>
</tbody>
</table>

$df = 68$ $\chi^2 = 775.83$ ($p=.00$)

As can be seen in Table 5, the interaction is evidenced significantly with a $t$-value of 8.15. However, the other two direct effects on Be, that of $PBC$ ($\gamma_1$) and that of $Int$ ($\gamma_2$) are not significant at the 5% significance level. Furthermore, the fit of the model is very poor. However, according to low modification indices, this is the best model we can get.

**Robust Maximum Likelihood Method (RML)**

As stated earlier, ML gives incorrect standard errors and Chi-squares because of the violation of the assumption of multi-normality. To solve this problem we consider a hybrid procedure, robust maximum likelihood (RML), where we apply a ML procedure to estimate the parameters and the asymptotic covariance matrix to obtain the correct standard errors and chi-square values.

Table 6 reports ML estimates with corrected standard errors and a corrected Chi-square.

After the correction none of the three $\gamma$s is significant. However, the Chi-square decreased quite considerably, but the model fit remained poor. Also here, low modification indices we got imply this is the best model we can get. As the results come out different from ML, one may wonder why. The explanation that we can give is that the method involved asymptotic covariance matrix that is computed from the fourth order moment for single indicators and eighth order moment for the product indicators. To get this asymptotic covariance properly estimated one really needs a very large sample size,
which we don’t have. It does not mean that one should not trust the results, it only shows this method is technically very difficult.

Table 6

RML Estimates of $\gamma$

<table>
<thead>
<tr>
<th></th>
<th>$\gamma_1$</th>
<th>$\gamma_2$</th>
<th>$\gamma_3$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Estimates</td>
<td>0.11</td>
<td>0.08</td>
<td>0.07</td>
</tr>
<tr>
<td>Standard errors</td>
<td>4.63</td>
<td>1.54</td>
<td>0.93</td>
</tr>
<tr>
<td>T-values</td>
<td>0.02</td>
<td>0.05</td>
<td>0.08</td>
</tr>
</tbody>
</table>

$\chi^2 = 328.3 \ (p=.00)$

Conclusion

In this paper, we tested the interaction effect between Intention and PBC in the theory of planned behavior with different methods. Reviewing research on this topic in a meta-analysis, we found out that about half of the studies (8 out of 14) that tested the interaction, indicated no significant effect. However, those papers used OLS techniques to test it. We do not trust regression results, because they assume that there are no random and non-random measurement errors. Jaccard and Wan (1995) pointed out why structural equation modeling, which controls for measurement errors, is preferred. Three studies in the meta-analysis applied more advanced techniques based on structural equation modeling (SEM), such as a multi-group analysis or ML. All of them found a positive interaction effect (according to what the theory postulates) and two of them found evidence also for a negative interaction. As stated in the paper, one possible reason for receiving a negative interaction effect could be due to multicollinearity. Another reason could be the content and measurement mode of the constructs’ items. Our own study found in two of the three estimation methods applied a positive interaction effect.

The question is whether one should consider in a meta-analysis all studies, or only those applying appropriate estimation techniques, which control for measurement errors using structural equation modeling. As Lipsey and Wilson (2001, p. 16) discuss it:

“The major exceptions are findings generated by multivariate analysis, e.g., multiple regression ... factor analysis, structural equation modeling and the like. Meta analysts
have not yet developed effect size statistics that adequately represent this form of research findings and, indeed, their complexity as well as diversity across studies with regard to the selection of variables involved may make this impossible”. Even if one takes into the meta-analysis only studies using estimation methods which control for measurement errors, different studies may report a variety of correlations: between indicators, indices or factors. Moreover, different estimation methods may be used, such as a multi-group analysis, ML, RML, TSLS, WLS, LVS and so on. Results may not be robust over studies, and different methods may produce different results with the same data as we evidenced here.

One may conclude, that conducting a meta-analysis is an impossible mission. We believe, that all studies should be taken into account in such a report. However, one should also report the estimation methods used. One way to overcome the problem of mixed estimation methods in the future might be to recalculate the results of the studies in the meta-analysis using the same method over all the data sets.

In this study we chose LVS, ML and RML to test the interaction. We reported in the introduction our main reasons for choosing these methods for the test. The fit measures of the RML and the ML estimation methods were poor. However, as we only wanted to test the interaction model, we did not try to improve them. The results are summarized in Table 7:

Table 7  
Summary of Results

<table>
<thead>
<tr>
<th>Additive effects</th>
<th>Interaction effects</th>
</tr>
</thead>
<tbody>
<tr>
<td>PBC</td>
<td>Intention</td>
</tr>
<tr>
<td>LVS</td>
<td>0.075*</td>
</tr>
<tr>
<td>ML</td>
<td>0.11</td>
</tr>
<tr>
<td>RML</td>
<td>0.11</td>
</tr>
</tbody>
</table>

* P < .05.

1. The LVS estimation evidenced a significant interaction between intention and PBC on behavior and significant additive terms. This is a simple method. It can be used to get a preliminary sign of an interaction effect. Since it is a two-step method, there is no overall model fit available. Although this method does not require multi-
normality for the observed variables, it does require more indicators for the latent variables. Put differently, the more indicators a latent variable has, the better the estimated score will be. Evaluation of this method is needed.

2. The ML estimation indicated an interaction effect between intention and PBC in predicting travel mode choice. However, the standard errors and Chi-squares were in principle incorrect because of the use of product variables.

3. RML was used to correct the standard errors and the Chi-square. It showed neither an evidence of a significant interaction nor significant additive effects. This method does give corrected standard errors and Chi-squares, but it requires considerably large samples. However, such samples are not always available, especially in Psychology.

From the results of the meta-analysis and from our own study we noticed that the different methods might lead to different results. Researchers may wonder which method to apply. From the simplicity point of view, we would suggest you to use multi-group analysis, (see McArdle, 2000; Yang-Jonsson 1997, 1998; Yang-Wallentin, Schmidt, & Bamberg, 2001). If the interaction variable is latent, the latent variable scores (LVS) approach or the two-stage least squares (TSLS) approach are probably the most reasonable (see Jöreskog, 1998; Yang-Wallentin, 2001). All these three approaches have no special requirement for the distribution of variables, they are easy to implement, and they can clearly indicate whether there is an interaction or not. The disadvantage is that none of these approaches provides a model fit. In the case of a multi-group analysis, we also do not get any coefficient for the interaction effect.

The full information methods do provide a parameter estimate for the interaction and an overall model fit. However, in practice they are difficult to apply due to the complicated non-linear constraints that must be specified and the necessity to have large samples and to use an asymptotic covariance matrix. The multi-normality of observed variables is required in order to apply a ML estimation method, but most non-linear models do not fulfill it. As a result of the violation of normality, the standard errors and $\chi^2$ are wrongly estimated. However, according to Yang-Jonsson (1997), ML often performs well in medium and large sample sizes.

For small samples, TSLS, LVS and Klein and Moosbrugger’s method (2000) are better. As LVS is very new, simulation studies that compare these methods are still missing. For large samples, RML and WLS are preferred, but further simulation studies are needed to compare them.
References


Appendix A

The measurement model is estimated by WLS. If one wants to choose a ML method instead, the asymptotic covariance matrix is not needed then.

Test Measurement Model
Observed Variables:
PBC1  PBC2  INT1  INT2  INT3  BEHAV
Sample size: 913
Latent Variables:
Pbc  Int  Behav
Covariance matrix from file measure.cm
Means from file measure.me
Asymptotic covariance matrix from file measure.acc
Relationships:
PBC1 = 1 * Pbc
PBC2 = Pbc
INT1 = 1 * Int
INT2 - INT3 = Int
Behav = Int Pbc
BEHAV = 1 * Behav
Set error variance for BEHAV to zero
PATH DIAGRAM
End of problem

Appendix B

When ML is used one does not need to read AC (Asymptotic covariance matrix). To run RML the exclamation mark in front of AC must be taken away.

Fitting Traffic Model to Mean Vector and Covariance Matrix by ML
DA NI=12 NO=912
LA
BEHAV  PBC1  PBC2  INT1  INT2  INT3  PBCINT11  PBCINT12  PBCINT13  PBCINT21  PBCINT22
PBCINT23
CM=LIMITNEW.CM
ME=LIMITNEW.ME
!AC=LIMITNEW.ACC
SE
2 3 4 5 6 7 8 9 10 11 12 1
MO NX=12 NK=3 TD=SY TX=FR KA=FR
LE
Behav
LK
Pbc  Int  IntPbc
FR LX(2,1) LX(4,2) LX(5,2) LX(12,1) LX(12,2) LX(12,3) PH(1,1)-PH(2,2)
FI PH(3,1) PH(3,2)
VA 1 LX(1,1) LX(3,2) LX(6,3)
FI KA(1) KA(2)
CO LX(6,1)=TX(3)
CO LX(6,2)=TX(1)
CO LX(7,1)=TX(4)
CO LX(7, 2) = TX(1) * LX(4, 2)
CO LX(7, 3) = LX(4, 2)
CO LX(8, 1) = TX(5)
CO LX(8, 2) = TX(1) * LX(5, 2)
CO LX(8, 3) = LX(5, 2)
CO LX(9, 1) = TX(3) * LX(2, 1)
CO LX(9, 2) = TX(2)
CO LX(9, 3) = LX(2, 1)
CO LX(10, 1) = TX(4) * LX(2, 1)
CO LX(10, 2) = TX(2) * LX(4, 2)
CO LX(10, 3) = LX(4, 2)
CO LX(11, 1) = TX(5) * LX(2, 1)
CO LX(11, 2) = TX(2) * LX(5, 2)
CO LX(11, 3) = LX(2, 1)
CO PH(3, 3) = PH(1, 1) * PH(2, 2) + PH(2, 1) * PH(2, 2)
CO TD(6, 1) = TX(3) * TD(1, 1)
CO TD(6, 3) = TX(1) * TD(3, 3)
CO TD(6, 6) = TX(1) ** 2 * TD(3, 3) + TX(3) ** 2 * TD(1, 1) + PH(1, 1) * TD(3, 3) + C
CO TD(7, 1) = TX(4) * TD(1, 1)
CO TD(7, 4) = TX(1) * TD(4, 4)
CO TD(7, 7) = TX(1) ** 2 * TD(4, 4) + TX(4) ** 2 * TD(1, 1) + C
CO TD(8, 1) = TX(5) * TD(1, 1)
CO TD(8, 5) = TX(1) * TD(5, 5)
CO TD(8, 6) = TX(3) * TX(5) * TD(1, 1) + LX(5, 2) * PH(2, 2) * TD(1, 1)
CO TD(8, 7) = TX(4) * TX(5) * TD(1, 1) + LX(4, 2) * LX(5, 2) * PH(2, 2) * TD(1, 1)
CO TD(8, 8) = TX(1) ** 2 * TD(5, 5) + TX(5) ** 2 * TD(1, 1) + PH(1, 1) * TD(5, 5) + C
CO TD(9, 2) = TX(3) * TD(2, 2)
CO TD(9, 3) = TX(2) * TD(3, 3)
CO TD(9, 6) = TX(1) * TX(2) * TD(3, 3) + LX(2, 1) * PH(1, 1) * TD(3, 3)
CO TD(9, 9) = TX(2) ** 2 * TD(3, 3) + TX(3) ** 2 * TD(2, 2) + C
CO TD(10, 2) = TX(4) * TD(2, 2)
CO TD(10, 4) = TX(2) * TD(4, 4)
CO TD(10, 7) = TX(1) * TX(2) * TD(4, 4) + LX(2, 1) * PH(1, 1) * TD(4, 4)
CO TD(10, 9) = TX(3) * TX(4) * TD(2, 2) + LX(4, 2) * PH(2, 2) * TD(2, 2)
CO TD(10, 10) = TX(2) ** 2 * TD(4, 4) + TX(4) ** 2 * TD(2, 2) + C
CO TX(6) = TX(1) * TX(3)
CO TX(7) = TX(1) * TX(4)
CO TX(8) = TX(1) * TX(5)
CO TX(9) = TX(2) * TX(3)
CO TX(10) = TX(2) * TX(4)
CO TX(11) = TX(2) * TX(5)
OU ME = ML AD = OFF MI SC