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Bayesian Latent Variable Models for Binomial Responses: Analysis of Schizotypal and Consumer Behavior Data from a University Study

By

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ΟΙΚΟΝΟΜΙΚΟ ΠΑΝΕΠΙΣΤΗΜΙΟ ΑΘΗΝΩΝ

ΤΜΗΜΑ ΣΤΑΤΙΣΤΙΚΗΣ

Μπεϋζιανά Μοντέλα Λανθανουσών Μεταβλητών για Διωνυμικά δεδομένα: Ανάλυση Σχιζοτυπικής και Καταναλωτικής Συμπεριφοράς σε δείγμα Φοιτητών και Σπουδαστών

Αθανασία Θεοδ. Οικονόμου

ΔΙΑΤΡΙΒΗ

Που υποβλήθηκε στο Τμήμα Στατιστικής

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ως μέρος των απαιτήσεων για την απόκτηση

Μεταπτυχιακού Διπλώματος Ειδίκευσης στη Στατιστική

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DEDICATION

...To my brother

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Athanasia Oikonomou

VITA

I was born in Korinthos where I lived until I was 18 years old when I finished the 2^{nd} high school. In 2000 I entered the department of Mathematics at the University of Ioannina. In Ioannina I lived until 2005 having the greatest experience of my life. In 2005 I came in Athens to continue my studies at the Master course of Statistics at the Athens University of Economics and Business.

ABSTRACT

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Bayesian Latent Variable Models

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The aim of this thesis is to examine whether impulsive and compulsive buying are related to the schizotypal personality characteristics. The Bayesian approach may be adopted to analyze the association between Schizotypal Personality Questionnaire (SPQ) scale and impulsive and compulsive responses of university students in Greece.

In Bayesian analysis all the available prior information of the data is used in combination with the data likelihood in order to calculate posterior distribution of the parameters of interest. Here statistical inference and interpretation of the parameters is solely based on their posterior distribution. However, usually it is difficult to calculate the posterior distribution of interest. In such cases modern computational methods such as Markov Chain Monte Carlo techniques are used to generate a sample from the corresponding posterior distributions of interest in which we can base our inference.

Firstly we present the latent factorial structure of schizotypal personality disorder as examined in the related bibliography. Several factor models are used to identify the latent structure of the data and represent hidden dimensions of Schizotypal Personality Disorder. Five models are compared via model selection criteria.

After analysing the latent structure of SPQ, we construct models to associate schizotypal data with impulsive and compulsive buying data. In our analysis we used the Binomial/ Logit model while in the related bibliography is used the normal one. Finally, having applied these models we observed that that there was no strong connection between comsuming behavior and schizotypy.

ΠΕΡΙΛΗΨΗ

Αθανασία Οικονόμου

Μπεϋζιανά Μοντέλα Λανθανουσών Μεταβλητών

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Στόχος αυτής της εργασίας είναι η διερεύνηση της πιθανής σχέσης μεταξύ παρορμητικής και καταναγκαστικής καταναλωτικής συμπεριφοράς και του σχιζοτυπικού χαρακτηριστικού ενός ατόμου. Η Μπεϋζιανη προσέγγιση υιοθετείται για την ανάλυση της κλίμακας σχιζοτυπικής συμπεριφοράς ΕΣΠ (SPQ) και των απαντήσεων σχετικά με αυθόρμητες και καταναγκαστικές συμπεριφορές σε ένα δείγμα Ελλήνων φοιτητών.

Στην Μπεϋζιανή ανάλυση χρησιμοποιείται όλη η διαθέσιμη εκ των προτέρων πληροφορία των δεδομένων (δηλαδή μη πληροφοριακών δεδομένων) σε συνδυασμό με την πιθανοφάνεια έτσι ώστε να υπολογιστεί η εκ των υστέρων κατανομή των παραμέτρων. Σε αυτή την προσέγγιση, η στατιστική συμπερασματολογία σε σχέση με τις υπό εξέταση παραμέτρους βασίζεται εξ ολοκλήρου στην εκ των υστέρων κατανομή. Ωστόσο συχνά είναι δύσκολο να υπολογιστεί η εκ των υστέρων κατανομή. Στην περίπτωση αυτή, σύγχρονες υπολογιστικές μέθοδοι όπως οι μέθοδοι προσομοίωσης MCMC παρέχουν την απαραίτητη εκ των υστέρων κατανομή και μας δίνουν την δυνατότητα να αναπαράγουμε ένα τυχαίο δείγμα στο οποίο μπορούμε να βασίσουμε την συμπερασματολογία μας.

Αρχικά, θα αναλύσουμε λανθάνοντα παραγοντικά μοντέλα της σχιζοτυπικής διαταραχής της προσωπικότητας σύμφωνα με αυτά που έχουν παρουσιαστεί ήδη στη σχετική βιβλιογραφία. Διάφορα παραγοντικά μοντέλα χρησιμοποιούνται έτσι ώστε να αποκαλύψουμε την λανθάνουσα δομή των δεδομένων και να αναπαραστήσουμε μέσα από ένα μοντέλο τις κρυμμένες διαστάσεις της σχιζοτυπικής διαταραχής της

προσωπικότητας. Πέντε μοντέλα που έχουν χρησιμοποιηθεί στη σχετική βιβλιογραφία συγκρίνονται μέσω κριτηρίων επιλογής του καταλληλότερου μοντέλου για να καταλήξουμε σε αυτό που περιγράφει καλύτερα τα δεδομένα μας.

Κατόπιν, συνδέουμε τα σχιζοτυπικά δεδομένα με τα δεδομένα της αυθόρμητης και της καταναγκαστικης καταναλωτικής συμπεριφοράς εφαρμόζοντας τρία μοντέλα για κάθε περίπτωση. Με αυτή την ανάλυση εξετάζουμε τη σχέση μεταξύ των σχιζοτυπικών χαρακτηριστικών και της καταναλωτικής συμπεριφοράς. Για την αναλυσή μας χρησιμοποιήσαμε το Binomial/ Logit μοντέλο ενώ στην βιβλιογραφία χρησιμοποιείται το κανονικό. Στο τέλος αυτά τα τρία μοντέλα συγκρίνονται και καταλήγουμε σε αυτό που καλύτερα περιγράφει αυτή την σχέση. Επίσης συμπεραίνουμε πως δεν υπάρχει ισχυρή σχέση αναμεσα στην καταναλωτική συμπεριφορά και την σχιζοτυπία.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

CHAPTER 1
INTRODUCTION

1.1 Introduction

The aim of this thesis is to facilitate binomial latent variable model to assess the effect of schizotypy on the consuming behavior expressed by impulsive and compulsive buying scales. Schizotypy is measured via a 74-item self administered questionnaire called the Schizotypy Personality Questionnaire (SPQ) introduced by Raine (1991).

The data of the survey of Iliopoulou (2004) are used in this thesis. The Greek version of SPQ (Stefanis et al., 2004) and a collection of items based on impulsive and compulsive buying were facilitated to associate schizotypy and buying behavior. All data were collected by students in Universities and Technological Educational Institutes in Greece.

In the first part of this thesis we review latent variable models for binomial data and their Bayesian implementation. Then we facilitate these models to initially explore the latent structure of schizotypy. The information available for schizotypy is aggregated in nine schizotypal traits: ideas of reference, odd beliefs or magical thinking, unusual perceptual experience, odd speech, suspiciousness, constricted affect, odd behavior, no close friends and social anxiety. We implement on schizotypal data five factor models which are presented in related bibliography. Then we identify the best one according to information criteria such as AIC and BIC. Since in the Bayesian approach statistical inference and interpretation of the parameters is based on their posterior distribution, computational sampling methods, such as Markov Chain Monte Carlo (MCMC) algorithms, are used to generate a sample from the corresponding posterior distribution.

Then, we examine the association of the schizotypal data with impulsive and compulsive buying. We extend the model that best describes the factorial structure of schizotypy by constructing a variety of models which associate impulsive and compulsive buying with schizotypal characteristics.

1.2 Latent Variables

In the present thesis, we are dealing with Bayesian Latent Variable Models (LVM). The Latent Variable Model (LVM) is a statistical model strongly related to the usual regression model. It relates a set of known (manifest) variables to a set of unknown ones (latent).

Latent variables are characteristics that underlie the observed measurements. They can not directly be observed but they are derived indirectly via other observable measurements called manifest variables. We can regard them as unobserved quantities which are expressed by manifest variables (Vittadini and Lovaglio, 2001). The main idea for developing LVM was that underlying and unobserved causes exist behind phenomena which are finally observed . The use of latent variables is common in social sciences. Some examples are: intelligence, academic performance, quality of life, business confidence, morale, happiness, conservatism and socio-economic status.

The main advantage of using LVMs is that we can reduce the dimensionality of a problem, aggregating information in a smaller dataset of latent variables often called factors (Bartholomew and Knott, 1999). Skrondal and Rabe-Hesketh, (2004, p.17) claim that latent variables are essential tools for our analysis because they generate distributions with desired variance. In addition, when dealing with problems from social sciences, it is convenient to consider some latent variables in order to represent quantitatively characteristics such as intelligence.

In present thesis, we are firstly exploring the latent structure of SPQ based on the Bayesian approach and then we associate schizotypy with consuming behavior which is expressed by impulsive and compulsive buying. All response data of this survey expressing schizotypy and consuming behavior are modeled using the Binomial distribution.

1.3 Bayesian approach

As we have already mentioned, in this thesis we adopt the Bayesian approach. Bayesian analysis is based on the principle that we can express our beliefs concerning parameters of interest using probabilistic statements. As a result, every unknown or unobserved quantity (parameter) can be treated as random variable (Gelman et al, 1996 p.12).

According to Bayesian methods, all decisions and related computations must be based on our prior beliefs and on observed information (data). On the contrary, statisticians following the classical approach, claim that inference becomes subjective by inserting our beliefs via the prior distribution (Carlin and Louis, 1996 p.5). In addition, Bayesian approach requires intensive computations. Bayesian computation was simplified in the early 1990's by the implementation of Markov Chain Monte Carlo (MCMC) algorithms (Carlin and Louis, 1996 p.5). These sampling based methods were implemented in a wide variety of problems and lead to the development of WinBugs which is programming oriented software for sampling from the posterior distribution of Bayesian models (Spiegelhalter et al, 1996).

In this thesis we consider the Latent Variable Models as hierarchical Bayesian models. In this case we consider both latent variables and parameters as random variables.

According to Fox and Glass (2001) Bayesian approach is the most favorable one in order to estimate the parameters of such models. It enables us to define a full probability model in order to quantify uncertainty in our study. Furthermore, results from previous studies and the data collection process can be included in the model. Secondly, under this procedure if some parameters are not fully determined, they can be specified over again using restrictions on them via their prior distributions. The last and most important advantage is that this procedure has been applied in Item Response models with multiple rates testlet structures latent classes and multidimensional latent abilities. Using MCMC methods for Bayesian inference, the multiple integrals that are incorporated in the complex dependency structures of the posterior distributions of interest can be efficiently estimated (Fox and Glas, 2001).

1.4 Structure of the thesis

The remaining of this thesis is organized in five additional chapters. Chapter 2 briefly reviews and describes concepts related to the Bayesian approach of Latent Variable Models. A theoretical framework of the Bayesian approach is also included and as well as description and definition of Latent Variable Models. Some estimation methods for LVM are briefly presented. Finally we conclude with a short description of MCMC algorithms. The next chapter presents impulsive- compulsive buying and schizotypy background information as presented in related bibliography.

Chapter 4 constitutes an intermediate stage of our final analysis. In this chapter, we explore the latent factorial structure of schizotypal personality disorder using the Binomial assumption in contrast to the normal assumption used in psychiatric research. Five models are implemented using WinBugs. The best one is selected according to information criteria such as AIC and BIC.

The selected factor structure of chapter 5 is the extended to accommodate the association between SPQ and consuming behavior resulting to six additional models (three for impulsive buying and three for compulsive buying). Finally we use information criteria to identify which describes best this association.

We conclude this thesis with a short discussion and a description of some topics that can be investigated for further research in chapter 6.

CHAPTER 2
BAYESIAN ANALYSIS OF LATENT VARIABLE MODELS

2.1 Latent Variable Model

A latent variable model relates a set of known observables, the manifest variables, to a set of latent ones. According to the type (continuous or categorical) of the latent and manifest variables, four types of latent variable models can be established namely:

- If both manifest and latent variables are categorical we have **latent class analysis,**
- If both manifest and latent variables are quantitative we have **factor analysis,**
- If the manifest variable is metrical and the latent is categorical, we have **latent profile analysis** and finally,
- If the manifest variable is categorical and the latent is metrical, we have **latent trait analysis.**

The above models are strongly related to the usual regression analysis model. In regression models we infer about the manifest variables given a set of other observable covariates and our goal is to explain the variance of the first one using the variance of the latter. In contrast, in Latent Variable Models (LVM) this relationship is inverted and our aim is to make inferences about the latent covariates given the manifest.

2.1.1 General Latent Variable Model

Suppose we have p manifest variables: $(x_1,...,x_p)$ and q latent variables: $(y_1,...,y_q)$ with prior distribution $\varphi(y)$. In the general case the model can be expressed as:

$$x_i = \alpha_{i0} + \sum_{j=1}^{q} a_{ij} y_j + \varepsilon_i, i = 1,..., p \tag{2.1}$$

under the assumptions:

$y_j \sim N(0,1)$,

$Cor(y_i, y_j) = 0, \forall i \neq j$,

$\varepsilon_i \sim N(0, \sigma_i^2)$, $Cor(\varepsilon_i, \varepsilon_j) = 0, \forall i \neq j$ and

$Cor(\varepsilon_i, y_j) = 0$.

Here α_{ij} denote the model parameter called loadings and reflect the correlations between latent and manifest variables (Bartholomew, Steele, Moustaki, Galbraith, 1999, p.150). The variance of x_i is simply given by the sum of squares of all loadings plus the variance σ_i^2. Hence:

$$Var(x_i) = \alpha_{i1}^2 + \alpha_{i2}^2 + ... + \alpha_{iq}^2 + \sigma_i^2$$

where σ_i^2 is the variance of the residuals and $\alpha_{i1}^2 + \alpha_{i2}^2 + ... + \alpha_{iq}^2$ represents the proportion of the variance of x_i explained by the factors of the model and is called communality (Bartholomew, Steele, Moustaki, Galbraith, 1999, p.152)

Here the goal is to reduce the dimensions of the problem from p to q and express the relations between the manifest variables using the latent ones. In the case the latent variables are uncorrelated to the manifest variables then these latent are sufficient for explaining all the dependencies between the manifest variables. In the opposite case, when this is not true then additional latent variables need to be added in order to fully explain all dependencies (Huber, 2003). This is called independence assumption.

Skrondal and Rabe-Hesketh (2004, p.3) comment on this property :*"A basic assumption of measurement models, both for continuous and categorical variables, is that the measurements are conditionally independent given the latent variable, i.e. the dependence among the measurements is solely due to their common association with the latent variable"*.

Assuming that the latent variables explain sufficiently the observed variables then their distribution considering that it is a member of the one parameter exponential family is the conditional $g_i(x_i \mid y_i)$:

$$g_i(x_i \mid y_i) = F_i(x_i) G_i(y_i) \exp(y_i u_i(x_i)) \tag{2.2}$$

for $i = 1,..., p$ and q<p

2.1.2 General Latent Variable Model for binary data

"*Binary responses are extremely common, especially in the social sciences. Individuals can be classified according to whether or not they belong to a trade union or take holidays abroad. They can be recorded as agreeing or disagreeing with some proposition or as getting some item in an educational test right or wrong"* (Bartholomew and Knott, 1999, p.77).

Binary responses usually are coded using zero-one coding with one usually expressing success or having a specific characteristic. In the case we have p items as for example in survey questionnaires then we have 2^p different response patterns. Let us suppose we have q latent variables $y = (y_1,..., y_q)$ and the p binary manifest variables: $x = (x_1,..., x_p)$ $x_i = \begin{cases} 1 \\ 0 \end{cases}$, $i = 1,2,..., p$.

If we assume multivariate standardized normal latent variables, that is: $y \sim N(0, I_n)$, then the binary data described above explain what this is and can be modeled by using a logit model:

$$\text{logit}\,\pi_i(y, \alpha_{ij}) = \alpha_{i0} + \sum_{j=1}^{q} \alpha_{ij} y_j \ , \tag{2.3}$$

where the probability $\pi_i(y)$ is denoted as:

$$\pi_i(y, a_{ij}) = P(x_i = 1 \mid y, a_{ij}) \ , \tag{2.4}$$

and is called the item response function (Bartholomew and Knott, 1999, p.78) and simplest the probability of success. The above model expresses the probability of a positive response to an item given the latent variable. Alternatively we can express equation (2.3) in terms of success probability. Hence we can write:

$$\pi_i(y, a_{ij}) = \frac{\exp(\alpha_{i0} + \sum_{j=1}^{q} \alpha_{ij} y_j)}{1 + \exp(\alpha_{i0} + \sum_{j=1}^{q} \alpha_{ij} y_j)} \tag{2.5}$$

The parameters α_{ij} are equivalent to the loadings of the general latent variable model described in section **2.1.1**. The parameter α_{i0} is usually called "intercept" due to its role in the plot of the $\log it \pi_i(y)$. Parameters α_{ij} are known as discrimination parameters because the bigger they are, the easier it will become to discriminate between a pair of individuals a given distance apart on the latent scale and reflects how steep is the curve of $\pi_i(y)$, in respect to changes of X_{ij} (Bartholomew and Knott, 1999, p.80). Here we have to assume that the p manifest variables are conditionally independent to the q latent variables, thus the conditional distribution is:

$$g(x_i \mid y) = \prod_{i=1}^{p} g_i(x_i \mid y) \tag{2.6}$$

The above conditional distribution is a Bernoulli distribution since our observables are binary, hence:

$$g_i(x_i \mid y) = \{\pi_i(y, a_{ij})\}^{x_i} \{1 - \pi_i(y, a_{ij})\}^{1-x_i} . \tag{2.7}$$

2.2 Bayesian Latent Variable Model

2.2.1 Introductory notions of Bayesian Inference

Here we shortly present the theoretical framework of the Bayesian approach including its characteristics starting with Bayes' Theorem**.** In addition in section 2.2.1.2 we provide a theoretical framework of predictive distribution.

2.2.1.1 Theoretical framework of Bayesian approach

"The Bayes' theorem provides a vehicle for changing or updating, the degree of belief about a parameter in light of more recent information" (Press, 1989, p.16). In its basic form is quite simple and refers on conditioning probabilities. Suppose we have two events A and B with $P(A) > 0$, then:

$$P(B \mid A) = \frac{P(A \mid B) P(B)}{P(A)} . \tag{2.8}$$

The position of events A and B can be inverted as a result probability of $A \mid B$ and $B \mid A$ are related.

We can have a more general case of Bayes' theorem if we consider the independent events $C_1, ..., C_k$ ($C_i \cap C_j \neq \varnothing$, $\forall i \neq j$, $i = 1, ..., k$ and $j = 1, ..., k$), which are a partition of the probability space Ω ($C_1 \cup ... \cup C_k = \Omega$). In this case we have

$$P(C_i \mid A) = \frac{P(A \mid C_i)P(C_i)}{\sum_{j=1}^{k} P(A \mid C_i)P(C_j)}, i = 1,...,k . \quad (2.9)$$

The above equation in terms of random variables and with f denoting the densities distributions can be translated to:

$$f(\theta \mid y) = \frac{f(y \mid \theta) f(\theta)}{\int f(y \mid \theta) f(\theta) d\theta} \quad (2.10)$$

where θ denotes the unobserved vector quantities or population parameters of interest and can be either discrete or continuous. The only difference is that in the discrete case the dominator would become:

$$\sum f(y \mid \theta_j) f(\theta_j) . \quad (2.11)$$

The observed data are denoted by y and can be either a continuous or a discrete variable. $f(\theta)$ represents the prior density or probability distribution function (i.e. the prior beliefs) in the continuous or discrete case respectively while $f(\theta \mid y)$ represents the posterior distribution of the parameter θ. The denominator is called "normalization constant".

An equivalent statement for the Bayes' theorem is:

$$f(\theta \mid y) \propto f(\theta) f(y \mid \theta). \quad (2.12)$$

In words, the posterior distribution is proportional to the prior distribution multiplied with the likelihood function, i.e. Posterior $\propto$ Prior $\times$ Likelihood.

The main characteristics of Bayesian approach are presented below as these were mentioned by Dellaportas and Tsiamyrtzis (2006). These are:

- **Prior information:** One of the most important components of Bayesian theory is the prior beliefs that must be incorporated to the inference of the problem.
- **Subjective probability:** All the probabilities are subjective and dependent on a person's beliefs or knowledge about the situation under study. In addition all the conclusions are based on posterior distribution which depends on how we have defined the prior distribution.

- **Self-consistency:** Using parameters as random variables has the result the decision theory to be based on probability theory. Consequently, all inferences about parameters come from the posterior distribution in the form of probability.

The advantages of the Bayesian approach are:

- The most important advantage of the Bayesian Paradigm is that it leads to a straightforward construction of credible intervals and p-values for hypothesis testing with natural interpretation (Congdon, 2001).
- Bayesian methods offer a more effective approach to model estimation because of the success to incorporate all the relevant information, in order to minimize inefficiency and incoherence (process available information systematically).
- Using this approach we condition on the data and replicate over parameters. In contrast in classical statistics we condition on the parameters and replicate over the data.
- Bayesian approach does not violate the Likelihood principle according to which if we have two probability models with analogous likelihood function for any given sample of data, then we are led to the same inferences for θ .
- Using modern computational techniques we have the exact condition to infer about a parameter.

As we have already mentioned in Bayesian statistics all the inferences are based on the posterior distribution. Frequently it is difficult to evaluate it, because of the denominator which involves difficult integrations and summations.

MCMC methods were developed in order to simplify these evaluations and therefore they provide a valuable computational tool. Conditional simulation methodology generates samples from a "target" distribution. The basic concept here is to draw samples from a Markov chain which comes from a "target" distribution and will converge to a stationary distribution. When convergence is achieved this stationary distribution is the posterior. An important point here related to convergence is to know how many iterations and burn-in iterations we need. Burn-in iterations are the iterations which will be excluded from the final sample.

The most known MCMC algorithms are: the Metropolis-Hasting algorithms and a special case of this the Gibbs sampling (for more details see Appendix E).

2.2.1.2 Predictive Distribution

Let us now suppose we have a model, the observations X_i (in our case the observations are the nine schizotypal traits) and the parameters of the model θ. Gelfand et al. (1992) propose five functions which can be calculated for each observation and which include a comparison between this observation and its predictive distribution $p(X_i)$ (Spiegelhalter et al, 1996):

- The residual: $x_i - E(X_i)$.
- The standardized residual: $(x_i - E(X_i))/\sqrt{V(X_i)}$.
- The chance of getting a more extreme observation: $\min(p(X_i < x_i), p(X_i \geq x_i))$.
- The chance of getting a more "surprising" observation: $p(X_i : p(X_i) \leq p(x_i))$.

Then, two cases were proposed in order to define the predictive distribution from whether the data set creates a separate evaluation data or not (Spiegelhalter et al., 1996). In the case the data X_i create a separate evaluation dataset, then we have a "training set" $\underline{y}$, on which is based the posterior distribution. Moreover, considering that our observations X_i are conditionally independent to the y and to the set of unknown parameters θ, the predictive distribution is determined as:

$$p(X_i \mid \underline{y}) = \int p(X_i \mid \theta) p(\theta \mid \underline{y}) d\theta . \qquad (2.13)$$

In the case we do not have a separate evaluation set then the predictive distribution of X_i should be remainder of the data and be conditional on the model so as to fulfil "cross-validation". As a result, every observation x_i should have a distribution $p(X_i \mid \underline{x}_{\backslash i})$, where $\underline{x}_{\backslash i}$ is the total data set without x_i. Approximating the cross-validatory method we can use the methods of the separate evaluation set having replaced $\underline{x}$ by $\underline{y}$. The predictive distribution now is given by:

$$p(X_i \mid \underline{x}) = \int p(X_i \mid \theta) p(\theta \mid \underline{x}) d\theta \qquad (2.14)$$

Another important issue here is that when we repredict X_i we should remove the effect of x_i. This has to be done in the case we want to sample satisfactory from the predictive distribution (Spiegelhalter et al, 1996).

2.2.1.3 Goodness of fit

In order to evaluate the goodness of fit a model we use the chi-square test: X^2 which in our case this of schizotypal data, is given by:

$$\mathrm{X}^2 = \sum_{i=1}^{n} \frac{[x_{ij} - E(x_{ij})]^2}{Var(x_{ij})}. \tag{2.15}$$

We calculate the chi-square statistic test for our data x_{ij} (as given in 4.1) for which we have that $x_{ij} \sim Bin(n_j, p_{ij})$ and the chi-square statistic test for the replicated (predicted) data set for which we have that: $x_{ij}^{pred} \sim Bin(n_j, p_{ij})$ and is given by:

$$\mathrm{X}^2_{pred} = \sum_{i=1}^{n} \frac{[x_{ij}^{pred} - E(x_{ij}^{pred})]^2}{Var(x_{ij}^{pred})} = \sum_{i=1}^{n} \frac{(x_{ij}{}^{pred} - n_j p_{ij})^2}{n_j p_{ij}(1-p_{ij})}$$

We make inferences based on their difference which forms the variable $p-value$. This is a binary variable taking the value one when $\mathrm{X}^2_{pred} > \mathrm{X}^2_{obs}$ and zero otherwise. çhere:

$$\mathrm{X}^2_{obs} = \sum_{i=1}^{n} \frac{[x_{ij} - E(x_{ij})]^2}{Var(x_{ij})} = \sum_{i=1}^{n} \frac{(x_{ij}{}^{pred} - n_j p_{ij})^2}{n_j p_{ij}(1-p_{ij})}$$

A $p-value$ close to zero indicates a bad model since what is observed is away from what is expected from the model.

2.2.2 Bayesian Latent Variable Models

The prior beliefs concerning model parameters, in the form of prior distributions are used to improve the accuracy of parameter estimates. Usually we define a single prior distribution with fixed parameters but, in some cases, a distribution is further imposed on the prior parameters. In this case the prior parameters are called hyperparameters and describe the distributional characteristics of the prior beliefs (Kim et al, 1994).

In this section we consider the latent variable models as hierarchical Bayesian models (Skrondal, and Rabe-Hasketh, 2004, p.205). When we deal with the Bayesian analysis of latent variable models, both latent variables and parameters are treated as random variables.

Fox and Glas (2001) believe that in multilevel models it is more advantageous to use latent instead of observed scores. They claim that: "*The advantage of using latent rather than observed scores as dependent variables of a multilevel model is that it offers the possibility of separating the influence of item difficulty and ability level and modeling response variation and measurement error. Another advantage is that, contrary to observed scores, latent scores are test- independent, which offers the possibility of using results from different tests in one analysis where the parameters of the IRT model and the multilevel model can be concurrently estimated*". Moreover, they support that: "*Latent scores are test-independent, which offers the possibility of analyzing data from incomplete designs, such as, for instance, matrix- sampled educational assessments, where different (groups of) persons respond to different (sets of) items*".

2.2.3 Parameter's estimation

Let us assume we have p manifest variables $(x_1,...,x_p)$ which represent our observations, q latent variables $(y_1,...,y_q)$ and the parameters of the model (2.3) α_{ij}. By the logit-model (2.3) the aim is to quantify the probability of answering positively to an item of the model considering the latent variables and α_{ij}.

The relation that expresses the probability of a positive response is:

$$\pi_i(y,\alpha_{ij}) = P(x_i = 1 \mid y, a_{ij}) = \frac{\exp\left(a_{i0} + \sum_{j=1}^{q} a_{ij} y_j\right)}{1+\exp\left(a_{i0} + \sum_{j=1}^{q} a_{ij} y_j\right)}$$

under the assumptions that the latent variables are normally distributed with mean zero and variance $\sigma_y^{\ 2}$, and the parameters α_{ij} are normally distributed variables.

$y_i \sim N(0, \sigma_y^{\ 2})$

$a_{ij} \sim N(0, \sigma^{2*})$

for i=1,…,p and j=1,…,q

Manifest variables are conditionally independent from latent variables and the parameters a-priori so that the conditional distribution is:

$$\pi(x_i \mid y, a_{ij}) = \prod_{i=1}^{p} \pi_i(x_i \mid y, a_{ij})$$

Since the observations are Bernoulli distributed, the conditional likelihood is given by:

$$\pi_i(x_i \mid y, a_{ij}) = \prod_i \prod_j \{\pi_i(y, a_{ij})\}^{x_i} \{1 - \pi_i(y, a_{ij})\}^{1-x_i}$$

The goal is to estimate the above parameters. Below we will discuss some methods that have been developed for that matter.

2.2.4 Estimation Methods

Several methods have been developed, based on Bayesian statistics for the parameters estimation. Kim et al (1994) proposed a method called "two joint Bayesian estimation" for the analysis of simulated data sets. This approach is used when we are not marginalizing over discrimination parameters. In the opposite case if we do so they propose the "two marginal Bayesian estimation". Compared with maximum likelihood estimates joint Bayesian estimates are more accurate as they are less biased.

2.2.4.1 Joint Bayesian estimation

Our model is:

$$\text{logit}\{\pi_i(y_j, a_{ij})\} = \text{logit}\{P(x_i = 1 \mid y_j, a_{ij})\} = a_{io} + \sum_{j=1}^{q} a_{ij} y_j = a' y \qquad (2.16)$$

where $a' = (a_{i0}, a_{i1}, ..., a_{ij})$ and $y = (1, y_1, ..., y_q)'$.

In the case of maximum likelihood estimation, we maximize the likelihood function $l(y,a \mid x)$ given by:

$$l(y,a \mid x) = \prod_{i=1}^{n} \pi(y,a)^{x_i}(1-\pi(y,a))^{1-x_i} = p(x \mid y,a) \tag{2.17}$$

In the approach of the joint Bayesian estimation, the estimates will accrue from maximization of the below posterior distribution:

$$\pi(y,a \mid x) = \frac{l(y,a \mid x)\pi(y,a)}{\pi(x)} \propto l(y,a \mid x)\pi(y,a), \tag{2.18}$$

where $\pi(y)$ represents the probability of positive response on the i-th item, $\pi(y,a)$ denotes the joint distribution of y and α and finally $\pi(x)$ represents the marginal likelihood function of x which is computed as:

$$\pi(x) = \int_{\mathrm{Y}}\int_{A} l(y,a \mid x)\pi(y,a)dady \tag{2.19}$$

where A and Y are the parameter spaces for the parameters α and latent variables y respectively.

The joint Bayesian approach of estimation is more favorable than the maximum likelihood estimation because provide us with parameter estimates which had smaller mean square differences from the underlying values, and were less biased (Kim et al, 1994).

2.2.4.2 Marginal Bayesian estimation

The marginal maximum likelihood of item parameters maximizes the marginal likelihood function $m(a \mid x)$ given by:

$$m(a \mid x) = \prod_{i=1}^{n} \int_{\mathrm{Y}} l(y_i, a \mid x_i)\pi(y_i)dy_i, \tag{2.20}$$

where $\pi(y_i)$ denotes the probability of positive response y_i.

The likelihood function is denoted as:

$$l(y_i, a \mid x_i) = \pi(y_i)^{x_i}(1-\pi(y_i))^{1-x_i} = p(x_i \mid y_i, a). \tag{2.21}$$

In this method, we maximize the marginal posterior distribution which is given by:

$$p(a \mid x) \propto m(a \mid x)\pi(a). \tag{2.22}$$

It is clear, in these methods that is, quite important to have flexible priors for our parameters. This can be ensured using appropriate transformation. These must be chosen such that they lead to a multivariate normal prior distribution. For this purpose, Mislevy (1986) proposed to transform the parameters a_j according to the logarithmic transformation, so: $\alpha_j = \log a_j$ and then estimate them.

So, for the vector of parameters a if we assume that these are independently distributed we have, $a \mid \mu_a, \Sigma_a \sim N(\mu_a, \Sigma_a)$:

$$\pi(a \mid \mu_a, \Sigma_a) = (2\pi)^{-n/2} |\Sigma_a|^{-1/2} \exp\left\{-\frac{1}{2}(a-\mu_a)'\Sigma_a^{-1}(a-\mu_a)\right\}.$$

2.2.4.3 Bayes modal estimation method

Mislevy (1986) developed a Bayesian theoretical framework for estimation in these models with two-stage prior distributions on both discrimination parameters and latent variables. Following the same assumptions as in the previous case and specifying that:

- y: follows normal distribution with mean μ_y and variance σ_y^2 and $\tau = (\mu_y, \sigma_y^2) \sim p(\tau)$.
- α: has density $p(a \mid \eta)$, where η is the parameter of α with density function $p(\eta)$.

If we assume that α and y are independent then the joint prior for all the unknown quantities is given by:

$$p(y, a, \tau, \eta) = \prod_i p(y \mid \tau) p(\tau) p(a \mid \eta) p(\eta). \qquad (2.23)$$

Applying Bayes theorem the posterior density function is given by:

$$p(y, a, \tau, \eta \mid x) = l(x \mid a, y) p(a \mid \tau) p(\tau) p(y \mid \eta) p(\eta). \qquad (2.24)$$

Where $l(x \mid a, y)$ denotes the likelihood function.

The above relation includes all the information available about the parameters of the model. According to Mislevy (1986) an important property is that the value of the posterior mean for any subset of parameters seems to remain unchanged with respect to marginalization of (2.16) over any subset of the remaining variables.

In cases of complex models the posterior means are not easily proceed, as a result they are approximated by the posterior modes which are easier in calculation. These are:

$$p(a,\tau,\eta \mid x) = \int p(y,a,\tau,\eta \mid x)dy \propto l(x \mid a,\tau)p(\tau)p(a \mid \eta)p(\eta)\,. \tag{2.25}$$

These modal estimates having a continuous and positive prior distribution tend to normality under regularity conditions like these of the maximum likelihood estimate (Mislevy, 1986).

2.3 MCMC computation

2.3.1 Introduction

The Bayesian approach is favored in latent variable models since MCMC algorithms can be applied in straightforward manner. MCMC methods provide us with techniques that we can use in different ways, depending on the inferences we are interested in. Albert and Chib (1993) and Patz and Junker (1999) developed a comprehensive theoretical framework based on these sampling algorithms and especially Gibbs sampler, for estimations on a latent variable model with binary responses; see in Appendix E for a short description of MCMC algorithms.

For the LVM of interest as defined in (2.8):

The posterior density $p(y \mid x)$ is given by:

$$p(y \mid x) = \frac{\pi(y)\prod_{i=1}^{p}\{\pi_i(y_j,a_{ij})\}^{x_i}\{1-\pi_i(y_j,a_{ij})\}^{1-x_i}}{\int \pi(y)\prod_{i=1}^{p}\{\pi_i(y_j,a_{ij})\}^{x_i}\{1-\pi_i(y_j,a_{ij})\}^{1-x_i}dy}\,. \tag{2.26}$$

where $\pi(y)$ is the prior density of y.

It is easily regarded that there is a relation between x's and y's. The logit binary regression model on x_i is connected with a normal linear regression model on y_j. The above connection has the advantage that makes easier to model uncertainty in a logit model using the hierarchical normal linear structure on y.

2.3.2 Gibbs sampling

The sampling method proposed by Albert and Chib (1993) is slightly modified from the classical approach. More specifically, Gibbs sampler (described in the first chapter) presumes simulating from the full conditional posteriors. But, in the case that these are not of a standard form, it is more difficult to perform the simulation.

To overcome this difficulty Albert and Chib's idea was to divide the posterior distribution π into *k mass points.* Then, instead of sampling from this continuous π to sample from the individual distributions as these have been emerged after the division. In other words, they proposed the parameters to be grouped in smaller subsets. These subsets must have the property that the conditional posterior distribution of each one parameter given all the others will be easily sampled via Gibbs sampling (Fox and Glas 2001).

Then, they introduced k independent variables $Z = (Z_{i1},...,Z_{ik})$ for the application of the sampler, under the assumptions that:

$$\begin{cases} x_{ik} = 1, & if \;\; Z_{ik} > 0 \\ x_{ik} = 0, & otherwise \end{cases}$$

The application of Gibbs sampler requires to sample:

- $Z^{(t+1)}$ from $p(Z \mid y^{(t)}, a^{(t)})$.
- $y^{(t+1)}$ from $p(y \mid Z^{(t+1)}, a^{(t)})$.
- $a^{(t+1)}$ from $p(a \mid Z^{(t+1)}, y^{(t+1)})$.

Patz and Junker (1999), claim that in order to have accurate estimates of a's we have to generate $y^{(t)}$'s and then discard them. In fact, when we do not use them it is like integrating them in other techniques. They compare their concept to the concept of "sufficient" statistics of y. These are not estimators of any quantity, but they are used to give "consistent" estimators of a's by conditioning on y's.

Supposing y's and a's are independent we have that:

$$p(y \mid x, a) = \frac{p(x \mid y, a) p(y, a)}{\int p(x \mid y, a) p(y, a) dy} \propto p(x \mid y, a) p(y), \tag{2.27}$$

$$p(a \mid x, y) = \frac{p(x \mid y, a) p(y, a)}{\int p(x \mid y, a) p(y, a) da} \propto p(x \mid y, a) p(a). \tag{2.28}$$

Actually, what is done here is, if we have some parameters to make inferences about one of them, assuming the others are unknown. If this property is iterated, then we manage to "adjust" inferences on a parameter for the uncertainty about the others.

2.4 Model Selection

In most cases we have to deal with complex hierarchical models we have to search which fits best our data by comparing them. For this purpose several methods have been developed in order to reassure us the best choice of model with the less cost. Here we will see three of them, these are: the Bayesian version of Akaike Criterion proposed by Akaike (1987), the Bayesian Information Criterion proposed by Schwartz (1978) and finally the Deviance Information Criterion introduced by Spiegelhalter et al.(2002).

The Bayesian version of Akaike Information Criterion (AIC) is defined as:

$$AIC = D(\hat{\theta}) + 2d^{*} \tag{2.29}$$

where d^{*} is the number of estimated parameters, the $\hat{\theta}$ denotes the posterior mean of the estimated parameters and finally the $D(\hat{\theta})$ is the estimate of the deviance at the posterior mean of the estimated parameters. The deviance generally is given by:

$$D(\theta) = -2\log f(y \mid \theta) \,. \tag{2.30}$$

where $f(y \mid \theta)$ represents the likelihood function.

The Bayesian Information Criterion (BIC) is defined as:

$$BIC = D(\hat{\theta}) + d^{*}\log(N)\,, \tag{2.31}$$

where N denotes the number of observed variables.

In fact, bearing in mind all the above the main comment is that the model with the smallest values of AIC or BIC is the model which best fits our data. Furthermore this model can best predict a replicate dataset of the same structure as the observed and finally will give us more accurate results.

CHAPTER 3
IMPULSIVE- COMPULSIVE BUYING AND SCHIZOTYPY

3.1 Introduction

In this project the aim is to analyze (within Bayesian framework) the relation between two different types of consumption –impulsive buying and compulsive buying- with the personality disorder known as schizotypy. Thus, firstly we are going to define and develop a theoretical framework for these concepts.

3.2 Impulsive buying

Impulsive buying denotes the unplanned buying which is any purchase a consumer does without having previous planning it (Stern, 1962). It is a "*focal point of considerable marketing management activity*" (Rook, 1987). Researchers find this consumer's behavior of great importance as this unplanned activity many times competes with the necessity to decrease the pleasure that buying provides. To sum up the above:

"Impulse buying occurs when a consumer experiences a sudden, often powerful and persistent urge to buy something immediately. The impulse to buy is hedonically complex and may stimulate emotional conflict. Also, impulse buying is prone to occur with diminished regard for its consequences" (Rook, 1987).

This topic has additional psychological aspects as makes it very easy to lose control. From psychological view impulse is a spontaneous action, more specifically is: "*a strong sometimes irresitable urge: a sudden inclination to act without deliberation*" (Goldenson 1984, p.34). It has been found out that it is correlated with age, intelligence and society in general. We are referred to society because is composed by its member's impulses and as Freud claim impulse is the combination of pleasure principle and reality principle. The pleasure principle is what enables people feeling instantly extremely pleased after a purchase, but this sensation dies out after thoughts for what they have done. This proceeding is the reality principle.

Impulsive buying is divided in four subcategories according to the factors that influenced it:

- **Pure impulse buying**: This is the case when the buyer has preplanned the place and the time of the purchases. As a result unnecessary actions are eliminated as much as possible.
- **Reminder impulse buying**: In this case the buyer when seew a product remembers that he must buy because does not have it, but he has previous experience of it.
- **Suggestion impulse buying**: Here, the consumer buys products without having seen them before and without any previous knowledge of them in total.
- **Planned impulse buying**: In this case, the buyer has some special needs and has planned to buy some products when entering a shop. Finally he manages to leave with many other purchases depending on prices and many other factors of the moment.

Many researches have shown that women are impulsive consumers since they consume in a spontaneous way. This phenomenon has been increased vastly during the last years since many people are planning for their purchases not at their homes but at the stores.

There are studies examining the circumstances under which people consume/ buy impulsively, resulting in a separation of products which are bought impulsely or not. There are several factors which explain this connection and categorize the products in total. Prices have the highest influence; low prices encourage people to impulse actions and, therefore, low priced products belong to the first category. In addition, the degree of need for a product, the number of available items, the self-service system of accommodation, advertisements or previous knowledge of the products, long or short life, small size or light weight, ease of storage for the products are also some factors for this point.

Furthermore, if we consider the separation of products in impulsive and non-impulsive items then we have to say that this tendency is now connected to some special categories of products. The above separation is one of the problems in impulsive consumption research since impulse is a person's and not product's characteristic. This tendency is highly associated to the price of products which is wrong. The second problem is that there is not a theoretical framework for researchers to be based on in order to develop and present their work.

3.3 Compulsive buying

3.3.1 Introduction

Let us start with a definition for compulsive buying or consumption. Compulsive buying was first defined by Emil Kraepelin (1915) when he tried to describe the problem of "buying mania" (Swan-Kremeier et al, 2006). Since then, many definitions describing this type of consumption have been considered. So, more recently compulsive consumption according to Faber, O'Guinn and Krych (1987, p.149, p.132) is: "*Chronic, repetitive purchasing that occurs as a response to negative events or feelings. The alleviation of these negative feelings is the primary motivation for engaging in the behavior. Buying should provide the individual with short term positive rewards, but result in long-term negative consequences*". In addition, it is an: "*inappropriate type of consuming behavior, excessive in itself, and obviously disturbing for the existence of individuals who seem to be prone to impulsive consumption*" (Valence, d'Astous, Forter, 1988).

Compulsive buying, in contrast with impulse buying is caused from an internal anxiety according to which buying shopping and spending is an "escape" (DeSarbo, & Edwards, 1996). The behavior of compulsive buyers is the result of extreme stress which leads to increased anxiety. People who act in this way want only to reduce their anxiety; they do not seek the possession of goods but the automatic reduction of their tension. In general, they want only to control their psychological tensions. They are characterized from strong emotional activation, high cognitive control and strong reactive behavior (Valence, d'Astous, Forter, 1988).

As in the previous case such a behavior is highly connected with personality aspects and the total environment the buyer is developing his personality. Edwards developed a framework for analyzing this tendency (Valence, d'Astous, Forter, 1988). She uses as factors the personality, family environment and credit cards if these exist. In addition, factors as low self-esteem, depression, dependency on others are of great importance for explaining compulsion. When we are referring to environmental factors we mainly mean advertising. Advertising takes advantage of people's emotions and needs and leads them to buying and consumption. Compulsive buyers in general are treated as personalities which buy in order to have the control of their selves.

3.3.2 Psychological aspect

Many researchers relate this behavior to factors responsible for other pathological disorders. These factors are: an extraordinary tendency and desire to consume, personal dependence, a total failure to control oneself and finally compulsive buying as a behavior is highly connected to psychological disorders.

Let us now discuss analytically the psychiatric aspect of this topic. Schlosser et al (1994), claim that compulsive buying can be related to other compulsive disorders of behaviors such as stress, neurosis phobia etc. They finally conclude that compulsive buying is a definable clinical syndrome which can cause its sufferers significant distress and is associated with significant psychiatric comordibity. In accordance to them Christenson et al (1994), arrive at a similar conclusion so they believe that compulsive buying results in psychological impairment and displays features of both obsessive disorders and the impulse control disorders (pathological gambling, pyromania and kleptomania).

Compulsive buying in general is an addiction, but taking into account psychiatric researches is one of simple addiction more "*homogenous model of substance addictions because these conditions may share clinical features and underlying brain circuitry and these features and circuitry do not alter by ingestion of exogenous substances*" (Hollander and Allen, 2006).

If this behavior is treated as a disorder then the advantages are:

- It will be included in surveys, so this will assist us estimate the prevalence rate of the disorder.
- We will be able to investigate the factors that lead to this disorder.
- Improve a characterization of brain-based circuits.
- The development of psychological and medical treatments.

Treating compulsive buying as a disorder has many benefits. Many scientists strongly object this approach. They support that this approach only favors pharmaceuticals companies (Hollander and Allen, 2006). In this thesis when we refer to a personality disorder related to the two types of buying, we mean the schizotypal personality disorder. In the following we briefly describe this disorder before we proceed to the data analysis in the next chapter.

3.4 Schizotypy

The term “schizotypy” was first used by Rado (1953) as a compaction of the terms “schizophrenic phenotype”. He defined this term in order to describe disorders supposed to be caused by genetic dispositions. These are:

- An integrative pleasure deficiency
- Proprioceptive diathesis, manifested in the form of an aberrant consciousness of the body, causing the appearance of distortions in the perception of body schema.
- Motivational deficit.
- Inability to organize goal-oriented activities.

For Rado diathesis is something common for schizotypy and schizophrenia so there is a clinical connection between them.

Schizotypy consists of several reliably identifiable factors, some of them are important for analysis because are responsible for disorders of schizophrenia (Giraldez et al, 2000). For Meehl (1962) the signs of schizotypy are:

- Cognitive slippage.
- Interpersonal aversiveness.
- Deficit in ability to experience pleasure.
- Ambivalence.

According to Meehl, schizotypy seems to be responsible for schizophrenia but the opposite does not hold. When all believed that the problem was caused by factors such as psychotic or psychophrenic relatives, he then claimed that there were not only the genetic factors, the social influences and clinical symptomatology that led to the clinical illness but furthermore there were other hypotheses. For this purpose, he introduced a model for researching the above relations. “*Schizotypy provides a tool for detecting fundamental features of liability to schizophrenia prior to the onset of clinical illness*”. Figure 3.1 describes the genetic diathesis for schizophrenia, schizotaxia and schizotypy and implied levels of analysis.

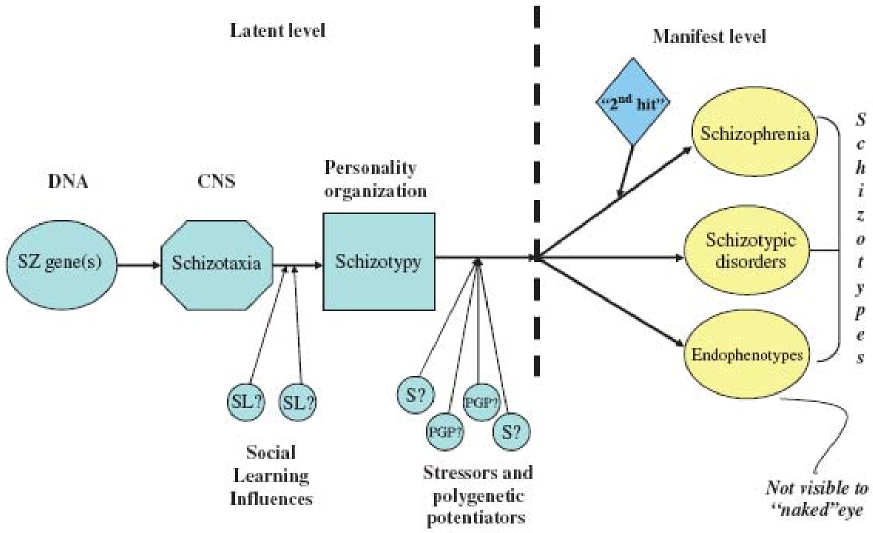


Figure 3.1 Developmental model relating the genetic diathesis for schizophrenia, schizotaxia, and schizotypy and implied levels of analysis (Lenzenweger, 2006)

Lenzenweger (2006) sets three approaches for defining schizotypy. The biologic approach relies on the idea that the relatives of a schizotypic person may have schizophrenic symptoms. The clinical approach is close to the psychiatric aspect of this problem and defines these persons according to the DSM-IV criteria. The third one is the laboratory approach which uses various measures that are indicators of schizophrenia liability.

Roth and Baribeau (2000) in their research relate this personality disorder to compulsive behaviors. They note particularly that schizotypal personality disorder (PSD) is highly connected with obsessive- compulsive disorder (OCD). In some researches has been concluded that the OCD results in some estimates and finally in occurrence of PSD and supplement that this relationship between the two types of disorder may be stronger for some characteristics.

In order to check if someone is schizotypal, we use the Schizotypal Personality Questionnaire (SPQ) from Raine (1991). This is a questionnaire composed by 74 questions designed in such a way in order to examine the nine factors defined by the American Psychiatric Association known as DSM- IV diagnostic criteria.

In a connection to the disorders described before according to the DSM-IV criteria defined by the American Psychiatric Association (1994) we have that: "*The essential feature of Impulse-Control Disorders is the failure to resist an impulse,* *drive, or temptation to perform an act that is harmful to the person or to others…the individual feels an increasing sense of tension or arousal before committing the act and then experiences pleasure, gratification, or relief at the time of committing the act. Following the act there may or may not be regret, self-reproach, or guilt*."

The DSM-IV diagnostic criteria are:

- **Ideas of reference:** A person with this disorder usually displays wrongly some events with special meaning for him.
- **Excessive social anxiety:** It is an anxiety that is not reduced by familiarity and is more connected to paranoid fears.
- **Odd beliefs or magical thinking:** These beliefs are superstitions, telepathy, obsessions, and fantasies. In general they are concepts from parapsychology.
- **Unusual perceptual experiences:** Sometimes they have the feeling that they are not alone in an empty place, or may feel unusual body experiences.
- **Odd or eccentric behaviour:** Eccentricity.
- **No close friends:** Not having close friends, they don't want to have friends or to be friends of others, they feel uncomfortable with everyone else except from members of their family.
- **Odd speech:** Absentminded thoughts, abstract speech.
- **Constricted affect:** The feeling of being different, and the difficulty in adaptability.
- **Suspiciousness:** The belief that others are trying to danger them.

In sequel the above nine criteria are band together in three subscale factors. The first factor is the **Cognitive-Perceptual factor** and is composed of; ideas of reference, odd beliefs, unusual perceptual experiences and suspiciousness. The second one is **the Interpersonal deficit factor** and is composed of; no close friends, constricted affect and excessive social anxiety. Finally, we have the **Disorganization factor** composed of; odd or eccentric behavior and odd speech. Here what we are going to do is to examine if the two types of buying are related to the characteristics of schizotypal personality and if so, with which characteristics there is a stronger relationship.

CHAPTER 4
ANALYSIS OF THE FACTOR STRUCTURE OF SPQ USING BAYESIAN LATENT VARIABLE MODELS

4.1 Introduction

The aim of this thesis is to analyze the latent variable structure of the schizotypy and impulsive/ compulsive data using the Bayesian paradigm. Especially, in our case we will examine how the consumer behavior is related to schizotypy. In the previous chapters of the thesis the theoretical framework required to analyze our data was described and discussed in detail.

The data of a student survey (Illiopoulou, 2004) will be analyzed in detail. A total number of 205 questionnaires were collected. In our analysis we focus on the 167 questionnaires fully completed (without any missing value) by university students. The data were collected in the School of Management Sciences of the University of Aegean (AEI) and Technological Education Institutes (TEI) of Crete and Piraeus.

The questionnaire was divided in five parts including three different scales for measuring the variables. The first part of the questionnaire includes seven questions (items) which measure impulsive buying under the coding of Likert ordinal scale (1-5). Furthermore, in this part, five additional items were used to measure compulsive buying using the same scaling.

The sample consisted of 56% females and 44% males, 57% of them are university students and 43% of higher technological educational institutes. Moreover the 91% were enrolled in a B.Sc course and 9% in a M.Sc course. Concerning the age of the students who participated in the survey, 54% of them are of the age 18-21, 38% between 22-25, and 7% between 26-29 and only 1% is over 30 years old. At percentage 91% responded that belong to a median economic level. The 80% of the students responded that are independent financially, in contrast to 12% responding that they are fully dependent financially to their families (see Appendix A for more details).

4.2 Factor analysis

In this section we examine five factor models based on psychiatric theory using the factor analysis in order to find out how many factors explain the schizotypal traits. The models under examination are the following:

- The one factor model,
- Kendler's two- factor model (Kendler et al, 1991),
- Raine's three- factor model known as the Disorganised 3-factor model (Raine et al, 1994),
- Stefanis four- factor model known as the Paranoid 4- factor model (Stefanis et al, 2004),
- The five- factor model proposed by Fogelson et al (1999).

Table 4.1 summarizes the structure of each factor model fitted to the schizotypal traits.

		Schizotypal traits								
MODEL	**FACTOR**	**IR**	**MT**	**UPE**	**S**	**SA**	**NCF**	**CA**	**OB**	**OS**
1-factor	Factor 1	#	#	#	#	#	#	#	#	#
Kendler's 2-factor	Positive	#	#	#	#	#				#
	Negative				#	#	#	#	#	
Disorganised 3-factor	Cognitive/ Perceptual	#	#	#	#					
	Interpersonal				#	#	#	#		
	Disorganised								#	#
Paranoid 4-factor	Cognitive/ Perceptual		#	#						
	Negative				#	#	#	#		
	Disorganised								#	#
	Paranoid	#			#	#				
Fogelson's 5-factor	Paranoid	#			#					
	Positive	#	#	#						
	Schizoid						#	#		#
	Avoidant	#				#				
	Disorganised				#			#	#	

Table 4.1 Table of factor models

(#:the factor is related to the schizotypal trait, IR: ideas of reference, MT: magical thinking (odd beliefs), UPE: unusual perceptual experiences, S: suspiciousness, SA: social anxiety, NCF: no close friends, CA: constricted affect, OB: odd behavior, OS: odd speech).

4.2.1 1-Factor model

The one-factor model is the simplest latent model available in the related bibliography. All the schizotypal traits are associated to one factor. This can be considered as a general measure/ scale of schizotypy. The figure below (Figure 4.1) represents the path diagram for the first model.

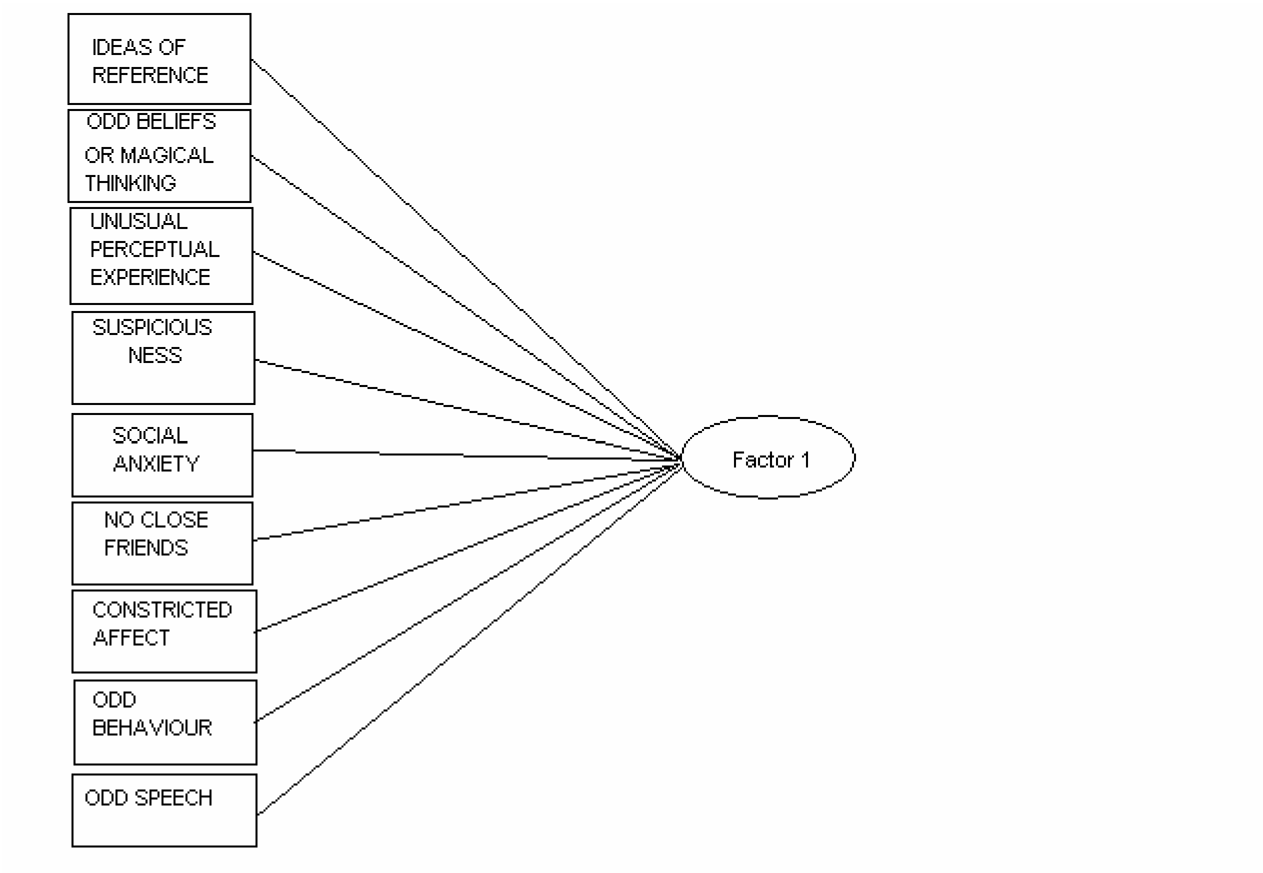


Figure 4.1 Path diagram for the one -factor model

4.2.2 Kendler's two-factor model

The idea of the two –factor model is based in the typical concept that schizotypy is composed by positive and negative characteristics /factors. The positive factor expresses the cognitive /perceptual disorder while the negative reflects the deficit in interpersonal function.

Kendler et al (1991) proposed a slightly modified two- factor model composed by a negative and a positive factor. Ideas of reference, odd beliefs or magical thinking, unusual perceptual experience and suspiciousness are related to the positive factor while no close friends, constricted affect, and odd behavior are related to the negative factor. In contrast to the traditional two- factor model where suspiciousness was loaded to the positive factor and social anxiety to the negative factor, Kendler and his associates claim that suspiciousness and social anxiety contribute to both factors. In addition they propose that the odd behavior belongs to the negative factor, in contrast to what was traditionally believed i.e. that it belongs to the positive factor; see Figure 4.2 for the path diagram of the two- factor model.

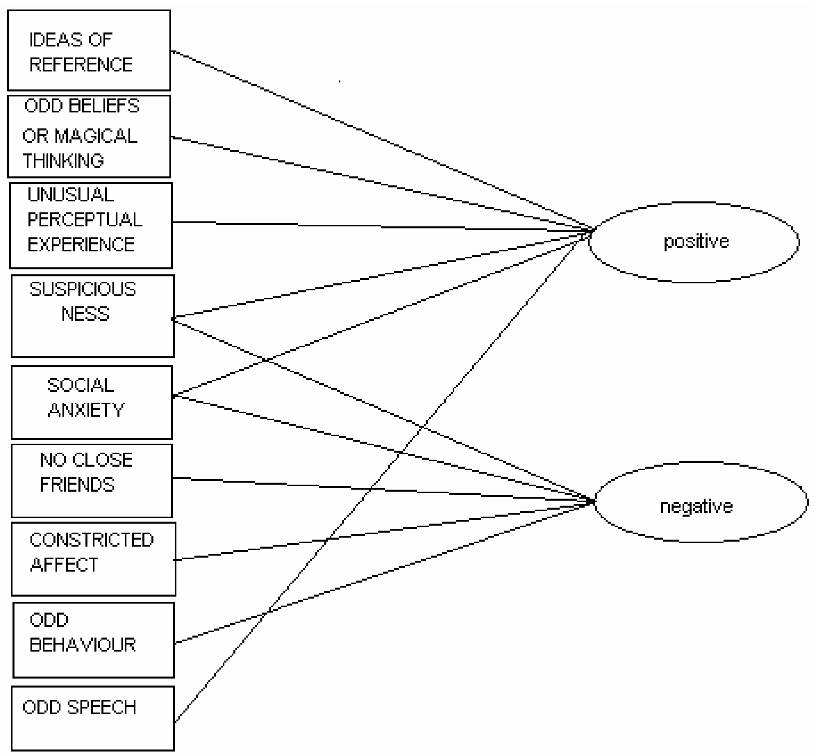


Figure 4.2 Path diagram for the two -factor model.

4.2.3 Disorganized three –factor model

The disorganized three –factor model was introduced by Raine et al (1994). The information available from the nine characteristics of schizotypy is summarized by three factors. The ideas of reference, the odd beliefs or magical thinking, the unusual perceptual experience and the suspiciousness constitute the cognitive /perceptual factor. This factor reveals the positive characteristics of the model. The negative characteristics are reflected in the interpersonal factor which is constituted by suspiciousness, social anxiety, no close friends and constricted affect. Finally, the last factor is the disorganized factor which reveals a behavior and cognitive disorder. Figure 4.3 represents the path diagram for the three –factor model.

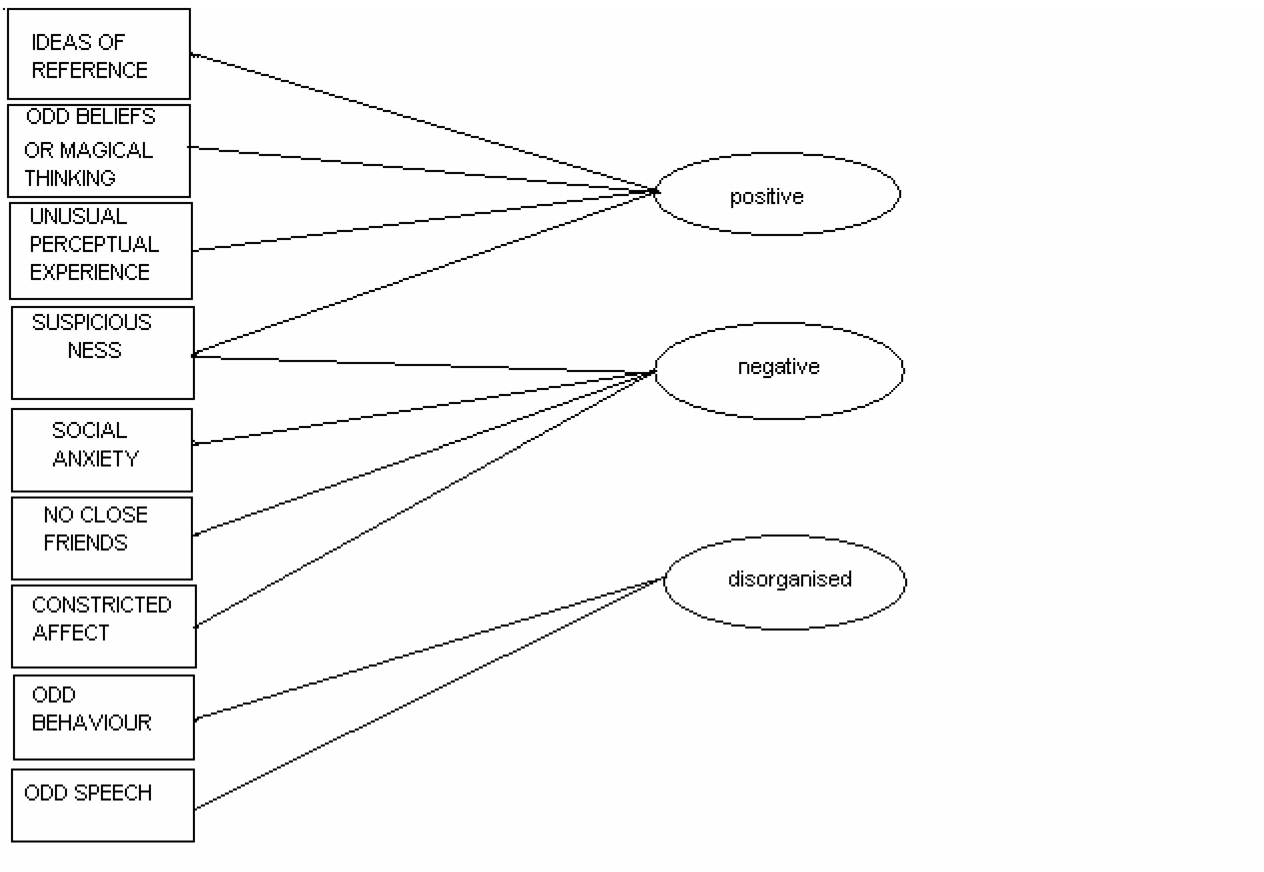


Figure 4.3 Path diagram for the Disorganized three -factor model.

4.2.4 Paranoid four-factor model

Stefanis et al (2004) proposed a four –factor model in order to model the nime characteristics of schizotypy. In fact they adopt a result appearing in several studies (Stuart et al., 1995; Kay and Sevy, 1990; Bassett et al., 1994; Penalta and Cuesta 1998, 1999). They propose to divide the positive factor of the two –factor model into two separated factors, the cognitive perceptual and the paranoid factor.

The odd beliefs or magical thinking and the unusual perceptual experience constitute the cognitive /perceptual factor. The paranoid factor is composed by ideas of reference, suspiciousness and social anxiety. The negative factor is composed by suspiciousness, social anxiety, no close friends and constricted affect. The disorganized factor is composed by odd behavior and odd speech; see Figure 4.4 for the path diagram of the four –factor model.

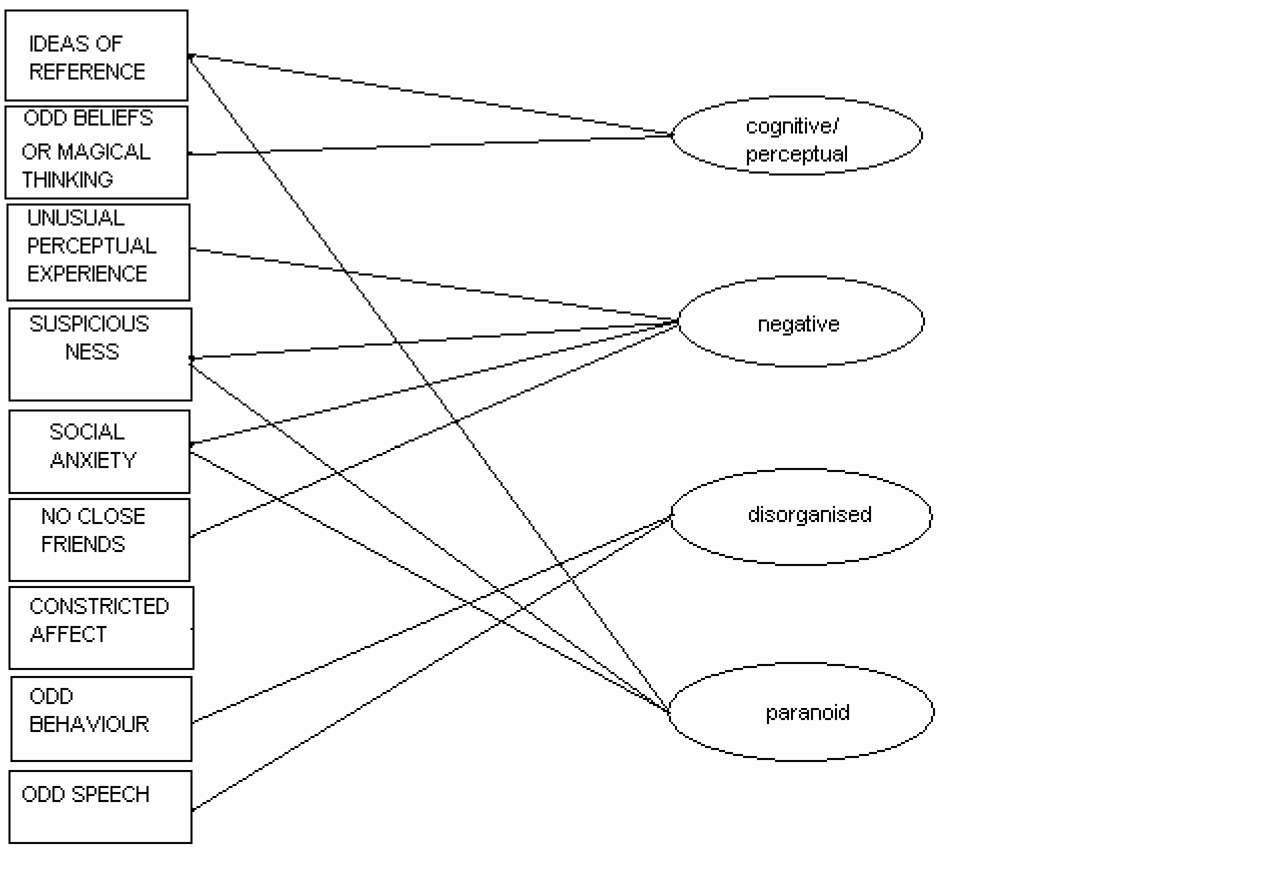


Figure 4.4 Path diagram for the Paranoid four -factor model.

4.2.5 The five –factor model

Fogelson et al. (1999) proposed the five latent factors in order to model the nine characteristics of schizotypy. These are the paranoid factor composed by ideas of reference and suspiciousness, the positive composed by ideas of reference, odd beliefs and unusual perceptual experience, the schizoid composed by no close friends, constricted affect and odd speech, the avoidant composed by ideas of reference and social anxiety and finally the disorganized factor composed by suspiciousness, constricted affect and odd behavior; see Figure 4.5 for a graphical representation of the five- factor model.

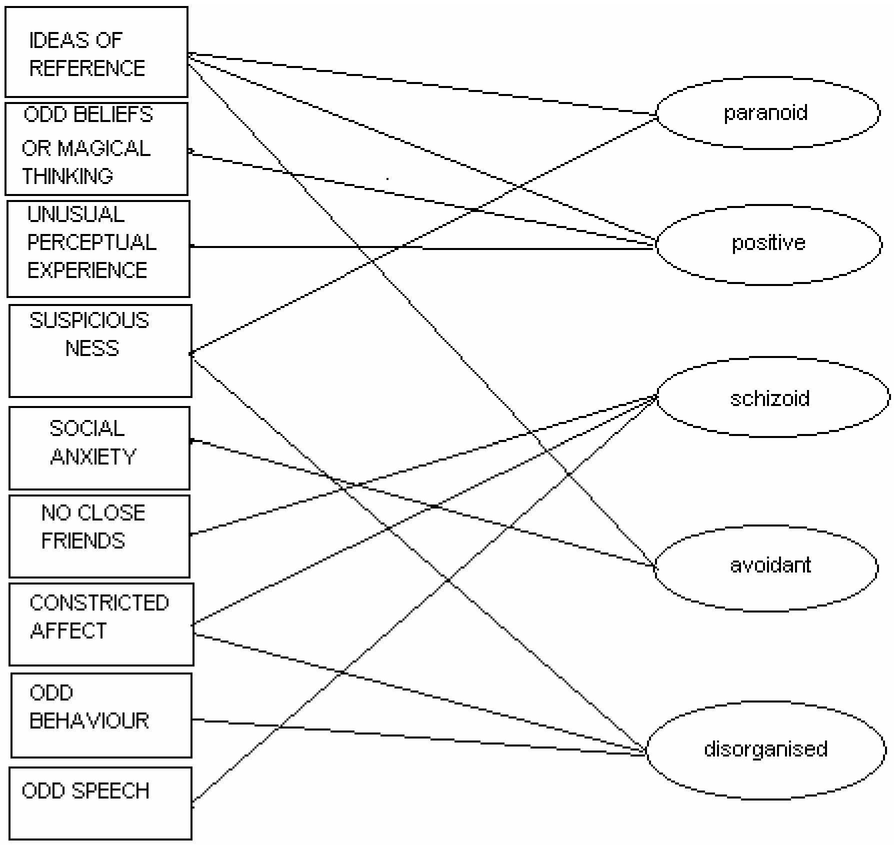


Figure 4.5 Path diagram for the five -factor model.

4.3 Analysis

4.3.1 Introduction

Five models were fitted to identify the structure of the schizotypal data. The general structure of the models is:

$$x_{ij} \sim Binomial(n_j, p_{ij}),$$

$$\text{logit}(p_{ij}) = a_j + \sum_{k=1}^{K} \gamma_{jk} l_{jk} f_{ik} + b_{ij}, \tag{4.1}$$

x_{ij} the number of positive responses of i subject for j SPQ subscale (i=1,…,167, j=1,…,9 and k=1,…,5). These are assumed to follow Binomial distribution with n_j denoting the number of items of the j-th SPQ subscale. In the above model we used the priors: $a_j \sim N(0,100)$ and $l_{jk} \sim N(0,1)$ where l_{jk} represent the parameter loadings of each model. In addition we have that:

$$\gamma_{jk} = \begin{cases} 1, \text{ if } f_k \text{ factor loads on j item} \\ 0, \text{ otherwise.} \end{cases}$$

The f_{ik} represent the factor score for i individual and k-th latent variable, for this we have assumed that $f_{ik} \sim N(0,1)$, while b_{ij} represent additional random effects components for which we assumed that $b_{ij} \sim N(0,1)$. A basic assumption of a constant a_j for every schizotypal trait is also adopted in the above models.

Models m_k for k=1,…, 5 are presented in Table 5.1. The distributions of both the factors and the random effects were assumed to be the standard normal distribution, while the random effects follow normal distribution. In addition, the priors of the factor loadings are assumed to be univariate normal distribution with some of them chosen to be truncated at zero.

For all the five models, we have generated 10000 burn-in iterations, and an additional sample of 20000 values using MCMC algorithms until our samples satisfy the convergence diagnostics described in chapter 1. For all models, generations of MCMC samples were performed using WinBUGS 1.4 (Spiegehalter et al., 2003)

4.3.2 Model Comparison

The five models were compared using the tço information criteria AIC, BIC and deviance presented in Chapter 3 (see section 3.4), considering as the number of free parameters to be the number of estimated factor loadings.

In all the cases the most appropriate model is the one with the smallest value. After generating MCMC samples via Winbugs we come up with the results presented in Table 4.2.

	AIC	BIC	deviance
model1	4417	4445	4403
model2	4412	4446	4397
model3	4416	4447	4398
model4	**4409**	**4443**	**4391**
model5	4414	4455	4398

Table 4.2 Information Criteria for the five models.
(AIC: Akaike Information Criterion, BIC: Bayesian Information Criterion).

From Table 4.2 the forth model (m_4) is the best model according to AIC and BIC. In both cases m_4 presents the smallest values as a result is the model chosen at this stage.

As the Paranoid four-factor model is chosen, in the next table the factor loadings for the m_4 are presented:

model4	**Factors**				
Schizotypal Traits	**Cogn/Perc**	**Negative**	**Disorganized**	**Paranoid**	α_j
Ideas of reference				0,568	-0,303
Odd beliefs or magical thinking	1,285				-0,485
Unusual perceptual experience	0,459				-1,015
Odd speech			0,806		-1,381
Suspiciousness	-0,024	0,817		1,456	-1,585
Constricted affect		0,754			-1,605
Odd behaviour			0,659		-0,675
No close friends		0,888			-1,585
Social anxiety		0,799			-0,764

Table 4.3 Factor loadings and constants for the Paranoid four- factor model.

The factor loadings are also referred as discrimination parameters. In addition, it is also known that the larger the values of l_{jk}, the greater is the effect of factor k on the probability of positive response to item j. Furthermore the higher the value of l_{jk} for an item the greater the difference in the probabilities of getting a positive response between two individuals who are located at same distance apart on latent scale. (Bartholomew, et al., 2002, p.183)

From Table 4.3 the relationships between factors and schizotypal traits are provided. In the case of the cognitive/ perceptual factor we can see that the log odds ratio of odd beliefs or magical thinking load strongly on this factor, while the effect of the log odds ratio of unusual perceptual experience on the first factor and finally suspiciousness is lower. Finally this factor has a very low but negative effect on the log odds ratio of suspiciousness.

In the second case of the negative factor, we can observe that the log odds ratio of all related traits are important affected by this factor. The same is also observed for the Disorganized factor where both odd speech and odd behaviour load heavily on the Disorganized factor. In the last case, we observe a strong effect of the Paranoid factor on the log odds ratio of suspiciousness. Smallest is regarded to be the effect of the paranoid factor trait on the log odds ratio of ideas of reference.

The fact that the loadings of the three last factors (the negative, the Disorganized and the Paranoid) are all positive implies that all the items of them have similar discriminating power and effect on each response. The last column of the Table 4.3 presents the values of the nine constants one for each trait.

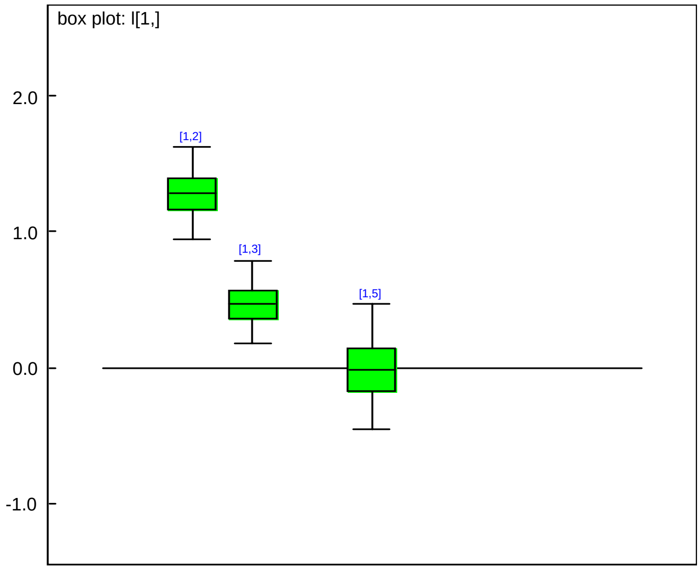


Figure 4.6 BoxPlot for the first factor of the Paranoid four factor model ([1,2], [1,3], [1,5] correspond to odd beliefs, unusual perceptual thinking, and suspiciousness respectively).

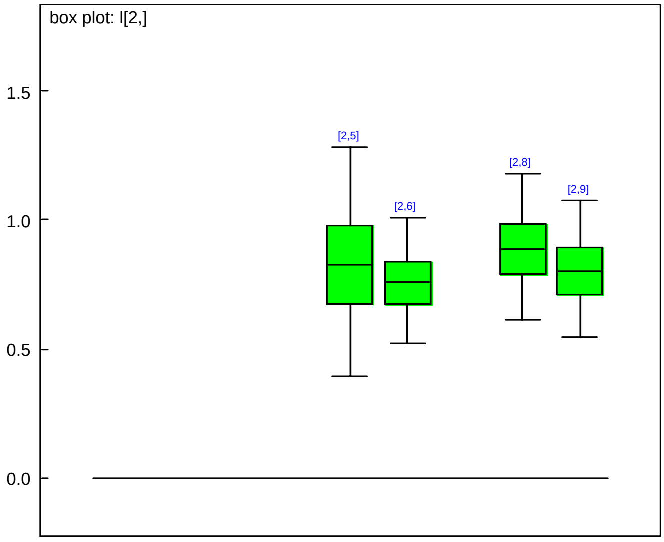


Figure 4.7 BoxPlot for the second factor of the Paranoid four factor model ([2,5], [2,6], l[2,8] , l[2,9] correspond to suspiciousness, constricted affect, no close friends and social anxiety respectively).

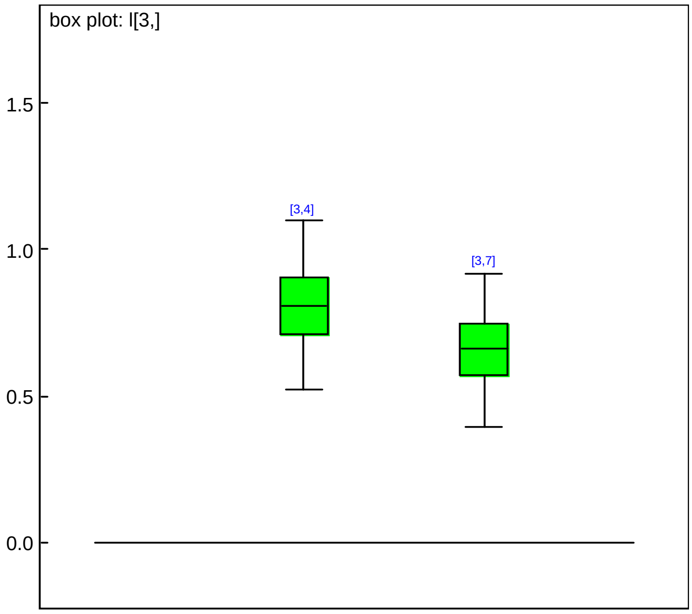


Figure 4.8 BoxPlot for the third factor of the Paranoid four factor model ([3,4], [3,7] correspond to odd speech and odd behaviour respectively).

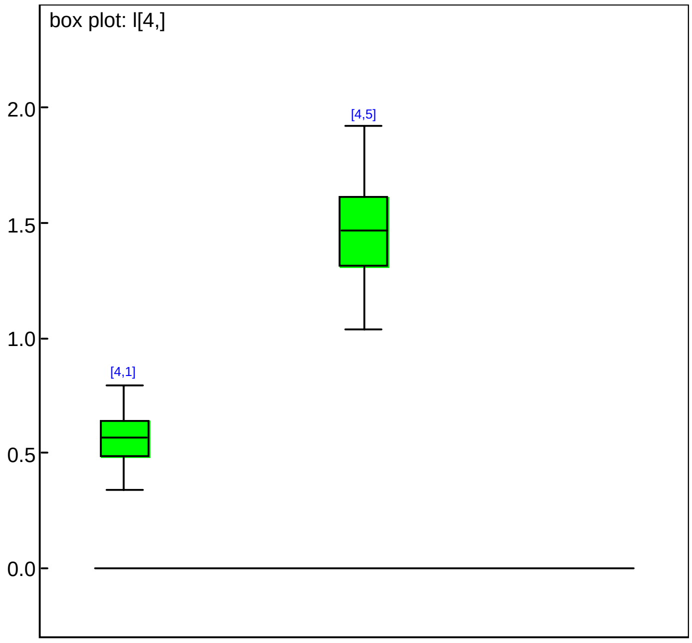


Figure 4.9 BoxPlot for the forth factor of the Paranoid four factor model ([4,1] , [4,5] correspond to ideas of reference and suspiciousness respectively).

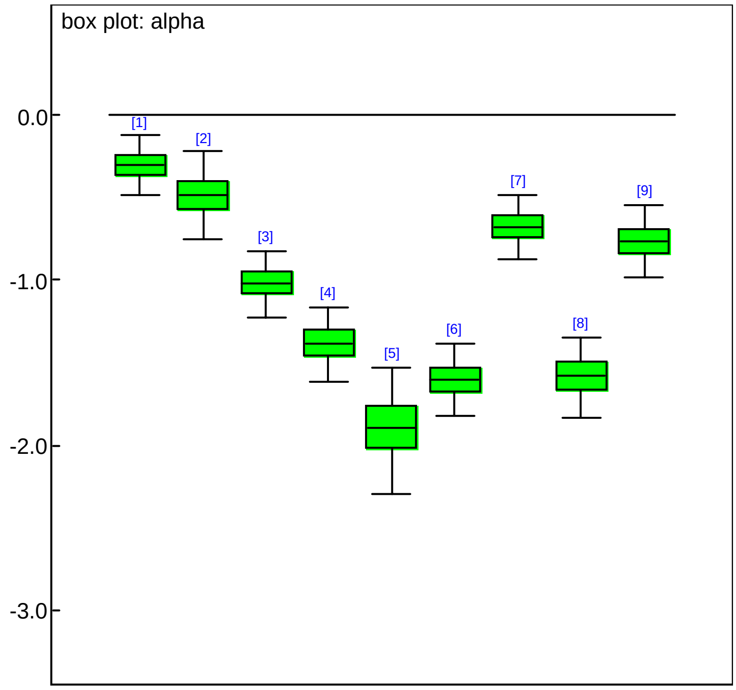


Figure 4.10 BoxPlot for the constants of the Paranoid four factor model ([1], [2], [3], [4], [5], [6], [7], [8], [9] correspond to ideas of reference, odd beliefs or magical thinking, unusual perceptual experience, odd speech, suspiciousness, constricted affect, odd behaviour, no close friends and social anxiety respectively).

Figures 4.6-4.9 represent the posterior means of each loading of the nine traits. Boxes are the inter- quartile ranges and the central line of each box we have chosen to be zero. In addition, the two edges of each box represent the 2.5% and the 97.5% quantiles. The ends of each box extend to cover the 95% of the posterior distribution. These boxes depict the 95% credible intervals of the quantities involved. (Spiegelhalter et al., 2003).

It is observed from the above five Figures that only in the case of the first factor (Figure 4.6) only one loading has posterior distribution dispersed around zero. The same is observed from the Table 4.3, where the effect of Cognitive/ Perceptual factor on suspiciousness cannot be considered as important. The corresponding posterior mean is very low (-0.024). We repeat our analysis removing this loading. All other loadings are high since all boxplots are far away from zero.

4.4 Model Fit

In order to check the model fit we will based on the predictive distribution. We use the chi-square test: X^2 as this is described in section 2.2.1.3.

In our case for the five factor models after the calculations we found that this $p-value$ for the five models is:

	$p-value$
model1	0,432
model2	0,440
model3	0,438
model4	0,442
model5	0,489

Table 4.4 Chi-square p-values for the five factor models.

As it was mentioned before a $p-value$ close to zero indicates a bad fit. However in our case from Table 4.4 it is observed that the five models have an acceptable fit, while the highest p-value is observed for the fifth model

4.5 Conclusion

In this chapter the first part of our analysis was presented in which we focus on the best fitted factor model of schizotypy. We provide posterior estimates and interpretation of the model.

Initially five factor models in the psychiatric research were presented. Then, based on information criteria (AIC/ BIC) we conclude to the Paranoid four- factor model as the most appropriate one to describe the latent structure of the schizoypy. It was concluded that the Negative, the Disorganized and the Paranoid factor have a strong effect on the log odds ration of their correspondent schizotypal traits. The Cognitive/ Perceptual thinking is observed to have strong effect on the log odds ratio of odds beliefs or magical thinking and unusual perceptual experience, while the same is not observed for the log odds ratio of suspiciousness where we have the opponent relation. The schizotypy model identified in this chapter will be used in the following chapter for further analysis.

CHAPTER 5
RELATIONSHIP OF IMPULSIVE- COMPULSIVE BUYING AND SCHIZOTYPY

5.1 Impulsive Buying

The questionnaire of the study comprehends five questions measuring impulsive buying. Each response was coded with values 1 to 5, with:

1- strongly agree

2- agree

3- neither agree nor disagree

4- disagree

5- strongly disagree.

To simplify the problem, values 1, 2 (which reflect agreement to the items statement) and 3 were recoded to zero (1), while values 4 and 5 (reflecting disagreement) were recoded to one (0) respectively. Before proceeding to modelling the recoded responses, we provide some initial statistics related to impulsive buying.

53% of our sample agrees that the expression “Just Do It” characterizes their buying behaviour; in contrast the 47% are not characterized by this expression. On the contrary, 58% of the participants disagree that they buy products without thinking of it. Even higher (79%) is the disagreement to the expression “Buy now, think of it later”. While the 65% agrees that he/ she react carelessly when buying. Finally, 75% of our sample is used to buy something that wants it immediately when sees it.

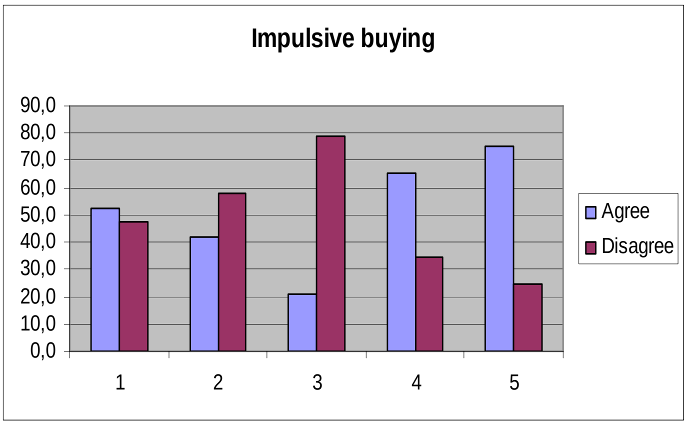


Figure 5.1 Diagram of percentages (1: Just do it, 2: Buy without thinking, 3: Buy now, think later, 4: React carelessly when buying, 5: Buy something that wants it immediately when sees it.)

Our next concern is to relate impulsive buying and schizotypy. In order to examine this relationship we will construct and fit three models using WinBugs vs. 1.4. In our analysis, for the models under consideration, we have generated 10000 burn-in iterations, and an additional sample of 20000 values via Gibbs sampling. Below, we describe in detail the theoretical framework for these models, the results of the analysis and finally related inference regarding our study data.

5.2 Models

5.2.1 Model 1

Firstly, we have constructed a model which relates impulsive buying with the nine schizotypal traits (5.1) and then is applied the model (5.2) which relates the four factors to the nine schizotypal traits. This model directly associates the observable variables while impulsive buying is indirectly related with the four latent factors. This relation is displayed by the figure below:

The first model is given by the following equation (see Appendix D, p.101):

$$imp_i \sim Binomial(n=5, p_i^{imp})\text{, i=1,…, 167.}$$

$$\text{logit}(p_i^{imp}) = a_0 + \sum_{j=1}^{p} a_j x_{ij} + b_i \tag{5.1}$$

with $x_{ij} \sim Binomial(n_j, p_{ij})$ being the schizotypal observations where n_j is the number of questions that are aggregated in its of the j schizotypal traits, j=1,…,9. In addition for the random effects we have that $b_i \sim N(0,\sigma^2)$. Finally the priors follow $a_0 \sim N(0,100)$ and $a_j \sim N(0,100)$.

In addition the nine schizotypal traits are modelled as in the previous chapter (4.1).

$$x_{ij} \sim Binomial(n_j, p_{ij})$$

$$\text{logit}(p_{ij}) = a_{2j} + \sum_{k=1}^{K} \gamma_{jk} l_{jk} f_{ik} + b_{2ij} \tag{5.2}$$

The above model represents the paranoid four-factor model which was selected as the most appropriate for fitting our data in the previous chapter. For i=1,…, 167, j=1,…,9 and k=1,…,5 here we have that $b_{2ij} \sim N(0,\sigma^2)$, $f_{ik} \sim N(0,1)$. For priors we used for this model: $a_{2j} \sim N(0,100)$ and $l_{jk} \sim N(0,1)$.

Posterior summaries of parameters effects a_j (j= 0,…, 9, eq.6.1) of the nine schizotypal traits on the log odds ratio and odds ratio of impulsive buying are presented respectively in Tables 5.1 and 5.2 as estimated from the MCMC output.

Model 1				
Schizotypal Traits	**means**	**s.d**	**2.5%**	**97.5%**
Ideas of reference	0.117	0.059	0.006	0.233
Odd beliefs or magical thinking	-0.039	0.043	-0.122	0.045
Unusual perceptual experience	-0.021	0.067	-0.109	0.154
Odd speech	-0.034	0.063	-0.156	0.089
Suspiciousness	-0.072	0.061	-0.191	0.047
Constricted affect	-0.016	0.078	-0.172	0.135
Odd behaviour	0.008	0.056	-0.099	0.118
No close friends	0.241	0.077	0.092	0.391
Social anxiety	-0.106	0.059	-0.223	0.009
α_0	-0.239	0.252	-0.729	0.253

Table 5.1 Posterior summaries of parameter effects of the nine schizotypal traits on the log odds of impulsive buying.

Model 1				
Schizotypal Traits	means	s.d.	2,5%	97,5%
Ideas of reference	1.126	0.067	0.999	1.262
Odd beliefs or magical thinking	0.962	0.041	0.885	1.046
Unusual perceptual experience	1.023	0.069	0.896	1.167
Odd speech	0.969	0.061	0.856	1.094
Suspiciousness	0.932	0.057	0.826	1.048
Constricted affect	0.987	0.077	0.842	1.144
Odd behaviour	1.010	0.057	0.905	1.125
No close friends	1.276	0.098	1.096	1.478
Social anxiety	0.901	0.053	0.800	1.009
α_0	0.813	0.208	0.482	1.288

Table 5.2 Posterior summaries of the odds ratios of impulsive buying for each schizotypal trait.

Model 2	Factors				
Schizotypal Traits	Cogn/Perc	Negative	Disorganized	Paranoid	α_{2j}
Ideas of reference				0,563	-0,308
Odd beliefs or magical thinking	1,274				-0,485
Unusual perceptual experience	0,463				-1,020
Odd speech			0,799		-1,384
Suspiciousness	-0,003	0,819		1,452	-1,893
Constricted affect		0,756			-1,607
Odd behaviour			0,652		-0,677
No close friends		0,884			-1,586
Social anxiety		0,792			-0,761

Table 5.3 Posterior means of factor loadings and constants for 5.2 model.

- The ideas of reference, odd behaviour and no close friends have a positive effect on the odds of impulsive buying as we can observe on Table 5.1. An increase of one point on these scales cause an increase of 12%, 1% and 27% respectively on the odds of impulsive buying (Table 5.2).
- In addition, the traits odds beliefs or magical thinking, unusual perceptual experience, odd speech, suspiciousness, constricted affect and social anxiety

have a negative effect on the odds of impulsive buying. These odds are decreased by 4%, 2%, 7%, 1.6% and 10% with an increase of one point in each scale respectively.

- Table 5.3 presents the factor loadings of the model 5.2 (the factor structure is the same as in the previous chapter). There are minor changes in the values of the factor loadings. From the corresponding values in the previous chapter (Table 4.4) we can conclude that these differences are minor. The interpretation of the model is the same as in the previous chapter.

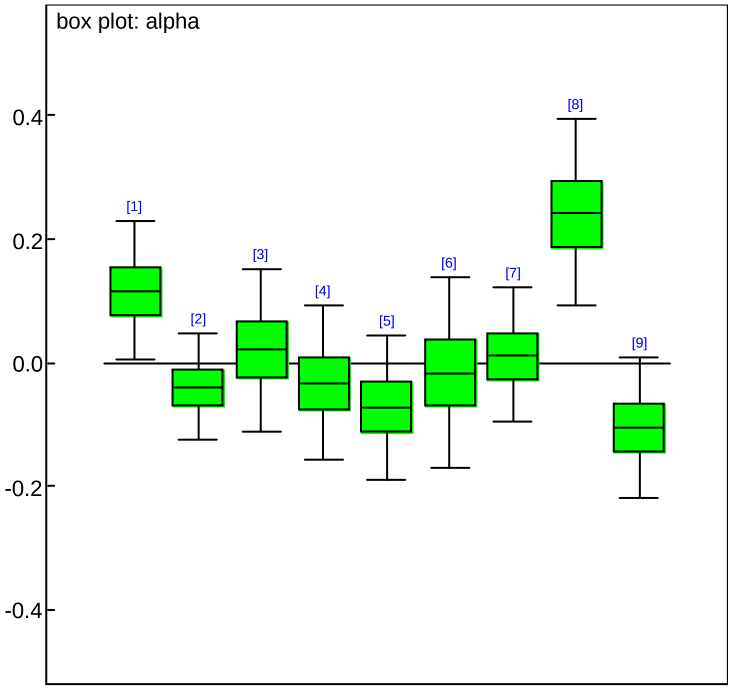


Figure 5.2 BoxPlot diagram for the nine parameters (schizotypal traits) of the model 5.1 ([1], [2], [3], [4], [5], [6], [7], [8], [9] correspond to ideas of reference, odd beliefs or magical thinking, unusual perceptual experience, odd speech, suspiciousness, constricted affect, odd behaviour, no close friends and social anxiety respectively).

Figure 5.2 depicts the boxplot for the parameters of the model. The plot has the same structure as in the previous chapter with the two edges of each box presenting the 2.5% and 97.5% quantiles (Spiegehalter et al., 2003).

From Figure 5.2 we observe that six of the parameters have posterior distribution dispersed around zero. The effect of them on the odds of impulsive buying can not be considered as important. In contrast, only a_1, a_8 and a_9 are a-posteriori away from zero. As a result ideas of reference, no close friends and social anxiety have a significant effect on impulsive buying.

5.2.2 Model 2

The second model we consider in this chapter relates impulsive buying with the four latent of schizotypy as these resulted by the Paranoid four-factor model presented in the previous chapter.

In this model we observe a direct relation between the four factors and the impulsive buying (5.3). In addition the four factors are also directly related to the nine schizotypal traits (5.4) as we can see below:

These relations are described by the following equation:

$$imp_i \sim Binomial(n = 5, p_i^{imp}),\ \text{i=1,…,167}$$

$$\text{logit}(p_i^{imp}) = \beta_0 + \sum_{k=1}^{4} \beta_k f_{ik} \tag{5.3}$$

with $f_{ik} \sim N(0,1)$ for k=1,…,4. The priors for this model are: $\beta_0 \sim N(0,100)$, $\beta_k \sim N(0,100)$. In addition for the random effects we have that $b_i \sim N(0,\sigma^2)$.

The second model is expressed by the Paranoid four-factor model we have seen previously:

$$x_{ij} \sim Binomial(n_j, p_{ij})$$

$$\text{logit}(p_{ij}) = \beta_{2ij} + \sum_{k=1}^{4} \gamma_{jk} l_{jk} f_{ik} + b_{2ij} \tag{5.4}$$

For the nine schizotypal traits we have that: $x_{ij} \sim Binomial(n_j, p_{ij})$ where n_j is the number of questions that are aggregated in its of the j schizotypal traits, j=1,…,9. Model (5.3) is the first model we apply here and model (5.4) the second. For the second model we have for the random effects that $b_{2ij} \sim N(0,\sigma^2)$. In addition we have assumed for the priors that $\beta_{2j} \sim N(0,100)$ and $l_{jk} \sim N(0,1)$. In table 5.4 are presented the posterior means of the factor loadings for the second model β_k and the constant β_0, as these are appeared after having run the model:

Model 1				
Schizotypal Traits	**means**	**s.d.**	**2.5%**	**97.5%**
Factor 1	-0.251	0.285	-0.755	0.341
Factor 2	-0.204	0.249	-0.733	0.253
Factor 3	0.230	1.011	-1.357	1.356
Factor 4	-0.340	0.356	-1.054	0.335
β_0	0.069	0.126	-0.181	0.316

Table 5.4 Posterior summaries of factor loadings for impulsive buying.

Model 1				
Schizotypal Traits	**means**	**s.d**	**2,5%**	**97,5%**
Factor 1	0.811	0.246	0.470	1.405
Factor 2	0.841	0.207	0.481	1.288
Factor 3	1.859	1.247	0.257	3.881
Factor 4	0.758	0.273	0.348	1.397
β_0	1.080	0.137	0.835	1.372

Table 5.5 Posterior summaries of factor loadings for the odds ratio of impulsive buying.

Model 2	Factors				
Schizotypal Traits	**Cogn/Perc**	**Negative**	**Disorganized**	**Paranoid**	β_{2j}
Ideas of reference				0.500	-0.306
Odd beliefs or magical thinking	1.187				-0.481
Unusual perceptual experience	0.505				-1.047
Odd speech			0.406		-1.329
Suspiciousness	0.051	-0.881		1.339	-1.870
Constricted affect		-0.734			-1.617
Odd behaviour			0.358		-0.668
No close friends		-0.881			-1.606
Social anxiety		-0.763			-0.768

Table 5.6 Factor loadings and constants for 5.4 model.

- The factor loadings here represent association parameter between the observed variable (impulsive buying) and the latent factors. For only the third factor a positive loading is observed. Hence, the third factor is associated with increased tendency to impulsive buying. Consequently, the log odds ratio of impulsive buying load strongly on the third factor. While the same is not resulted from the first, the second and the last factor. These present a negative effect on the log odds ratio of impulsive buying. They have negative values and especially the forth factor presents the largest in terms of absolute values -0.340. The posterior means loadings of factor 1 and factor 2 are equal to-0.251 and -0.204 respectively.
- Table 5.5 presents how the four latent factors affect the odds ratio of impulsive buying. We arrive at the same conclusion as in the case of Table 5.4. The effect of the odds ratio of impulsive buying is strongest in the case of the third factor since it displays the largest loading (1.859) indicating an increase of 86% at the odds of impulsive buying when factor 3 increases by one unit. For the rest of the factors the odds of impulsive buying decreases with a range between 16 and 24% for each unit increase of the remaining factors.
- Table 5.6 presents the factor loadings of the Paranoid four- factor model. There are changes in the values of the factor loadings from the corresponding values of the previous chapter. Therefore, the interpretation will be altered. It is observed that the log odds ratio of odds beliefs or magical thinking load strongly on the cognitive/ perceptual factor. Lowest seems to be the effect of the log odds ratio of unusual perceptual thinking and suspiciousness on this factor. For the negative factor, we observe that the log odds ratio of all its correspondent traits present a negative effect on it. In addition, for the last two factors we observe that the log odds ratio of their correspondent traits have a positive effect on them. Especially in the case of the last factor the log odds ratio of suspiciousness loads strongly on it.

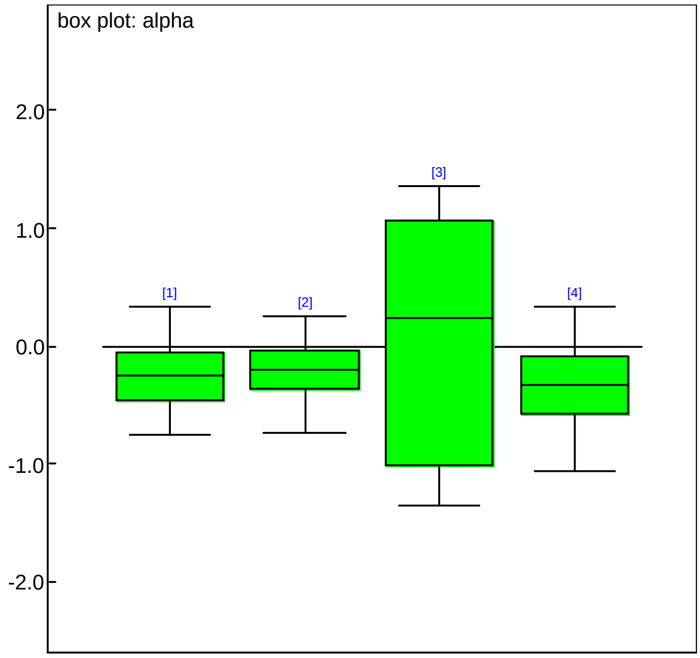


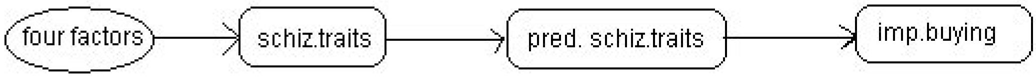
Figure 5.3 BoxPlot diagram for the parameters of the model 5.3 ([1], [2], [3], [4] correspond to factor 1, factor 2, factor 3 and factor 4 respectively).

Figure 5.3 displays the boxplot diagram for the four factors of the model. Here, we can conclude that none of the four factors is a- posteriori distributed away from zero. As a result, the effect of the four factors factor on impulsive buying seems to be minor and cannot be considered as important

5.2.3 Model 3

Finally, a third model based on the predictive posterior distribution is constructed (see section 2.2.2).

Here we have constructed a model relating impulsive buying and the predictive values of the nine schizotypal. By this way we add increased variability to the first model concerning the association between the two set of variables. In this model, impulsive buying and the predicted nine schizotypal traits are connected on a direct way (5.6). This implies an indirectly relation between impulsive buying and the initially observed schizotypal traits (5.7) (see Appendix D, 2.3).



The model is summarized by the following:

$$imp_i \sim Binomial(n = 5, p_i^{imp}), \text{ i=1,…, 167}$$

$$\text{logit}(p_i^{imp}) = a_0 + \sum_{j=1}^{9} a_j x_{ij}^{pred} + b_i \tag{5.6}$$

x_{ij}^{pred} are the predicted schizotypal traits coming from the predictive posterior distribution and they have the same distribution with x_{ij}: $x_{ij}^{pred} \sim Binomial(n_j, p_{ij})$, $x_{ij} \sim Binomial(n_j, p_{ij})$ j=1,…,9. In addition for the random effects we have that $b_i \sim N(0, \sigma^2)$. Finally the prior distributions of the model are: $a_0 \sim N(0,100)$ and $a_j \sim N(0,100)$.

The equation (5.6) relates the predicted schizotypal traits with impulsive buying. The second model applied here relates the schizotypal traits with the four factors and is given by:

$$x_{ij} \sim Binomial(n_j, p_{ij})$$

$$\text{logit}(p_{ij}) = a_{2j} + \sum_{k=1}^{4} \gamma_{jk} l_{jk} f_{ik} + b_{2ij} \tag{5.7}$$

The above model represents the paranoid four-factor model which was selected as the most appropriate for fitting our data in the previous chapter. For i=1,…, 167, j=1,…,9 and k=1,…,5 here we have that $b_{2ij} \sim N(0, \sigma^2)$, $f_{ik} \sim N(0,1)$. For priors we used for this model: $a_{2j} \sim N(0,100)$ and $l_{jk} \sim N(0,1)$.

In the next table the posterior means of the estimated factor loadings for the model (5.6) and the constant a_0 can be seen, as these can be seen after our analysis:

Model 1				
Schizotypal Traits-predictive	**loadings**	**s.d.**	**2.50%**	**9.75%**
Ideas of reference	0.182	0.114	-0.051	0.403
Odd beliefs or magical Thinking	-0.050	0.079	-0.206	0.109
Unusual perceptual experience	0.021	0.146	-0.280	0.301
Odd speech	-0.067	0.129	-0.321	0.192

Suspiciousness	-0.134	0.129	-0.389	0.128
Constricted affect	-0.008	0.168	-0.341	0.319
Odd behaviour	0.054	0.107	-0.153	0.266
No close friends	0.455	0.152	0.142	0.748
Social anxiety	-0.171	0.119	-0.404	0.065
α_0	-0.621	0.467	-1.522	0.306

Table 5.7 Posterior summaries of parameter effects of the predicted traits on the log odds of impulsive buying.

Model 1				
Schizotypal Traits	**means**	**s.d**	**2,5%**	**97,5%**
Ideas of reference	1.207	0.137	0.949	1.496
Odd beliefs or magical Thinking	0.954	0.076	0.814	1.116
Unusual perceptual experience	1.032	0.149	0.756	1.352
Odd speech	0.943	0.124	0.725	1.211
Suspiciousness	0.882	0.115	0.678	1.136
Constricted affect	1.006	0.169	0.711	1.377
Odd behaviour	1.061	0.114	0.858	1.305
No close friends	1.595	0.242	1.153	2.113
Social anxiety	0.849	0.102	0.668	1.067
α_0	0.599	0.293	0.218	1.358

Table 5.8 Posterior summaries of odds ratio of impulsive buying for each predicted schizotypal trait.

Model 2	**Factors**				
Schizotypal Traits	**Cogn/Perc**	**Negative**	**Disorganized**	**Paranoid**	α_j
Ideas of reference				0.801	-0.295
Odd beliefs or magical Thinking	1.164				-0.487
Unusual perceptual experience	0.499				-1.052
Odd speech			0.747		-1.392
Suspiciousness	0.058	1.449		0.003	-1.778
Constricted affect		0.641			-1.599
Odd behaviour			0.616		-0.681
No close friends		0.661			-1.548
Social anxiety		0.824			-0.777

Table 5.9 Factor loadings and constants for 5.7 model.

- The predicted traits ideas of reference, unusual perceptual thinking, odd behaviour and no close friends have positive effect on the odds of impulsive buying. An increase of one point on these scales cause an increase of 18%, 2%, 5% and 46% respectively on the odds of impulsive buying.
- Moreover, the predicted odd beliefs or magical thinking, odd speech, suspiciousness, constricted affect and social anxiety have a negative effect on the odds of impulsive buying. This odd decrease by 5%, 7%, 13%, 1% and 17% with an increase of one point in each scale respectively.
- Table 5.9 presents the factor loadings of the model 5.7. There are changes in the values of the factor loadings from the corresponding values of the previous chapter, however these are not significant. In all factors we observe that the log odds ratio of the correspondent predicted traits have an important effect on them. In some cases this effect seems to be stronger for instance first factor and odd beliefs or magical thinking (1.164), second factor and suspiciousness (1.449), fourth factor and ideas of reference (0.801). While, in other cases this effect is lower for instance in the case of the log odds ratio of suspiciousness and its effect on the first factor (0.058) and the fourth factor (0.003).

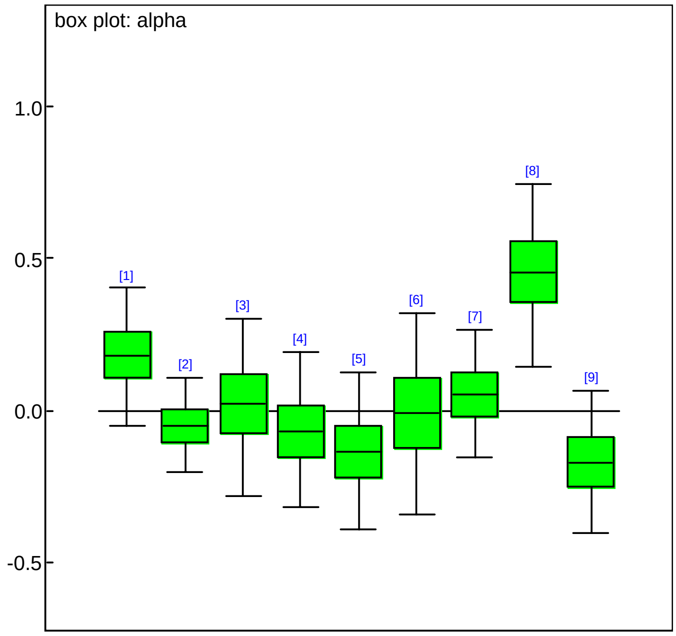


Figure 5.4 BoxPlot diagram for the nine parameters of the model 5.6 ([1], [2], [3], [4], [5], [6], [7], [8], [9] correspond to ideas of reference, odd beliefs or magical thinking, unusual perceptual experience, odd speech, suspiciousness, constricted affect, odd behaviour, no close friends and social anxiety respectively).

From Figure 5.4 we observe that six of the parameters have posterior distribution dispersed around zero. The effect of them on the odds of impulsive buying can not be considered as important. In contrast, only a_1, a_8 and a_9 are a- posteriori away from zero. As a result ideas of reference, no close friends and social anxiety have a significant effect on impulsive buying.

5.3 Models Comparison of the impulsive buying- schizotypy

In the previous section 5.2 three models were presented to describe the relation between impulsive buying and schizotypy.

The three models analyzed above are compared here using the information criteria AIC, BIC. In all the cases the most appropriate model is this one which seems to have the smallest value of the information criteria. After the calculations via WinBUGS we come up with the results presented in the Table 5.10.

	AIC	BIC	deviance
model1	4389	4417	4851
model2	4029	4057	4855
model3	3981	4009	4848

Table 5.10 Information Criteria for the three models assessing the association between impulsive buying and schizotypy.

It is easily observable from Table 5.10 that in the case of impulsive buying the best model, is the third model (model 5.6, see section 5.2.3.2). This is based for the calculations on the predictive posterior distribution of the latent factor model. It displays the smallest value of AIC and BIC information criteria. So, we can say that the replicate schizotypal traits have the greater influence to the probability of positive response in impulsive buying.

Although the third model is chosen as the best model to fit our data according to AIC/ BIC it is remarkable that according to chi-square statistic test (Table 5.11) the best fit is provided by the first model. However, the three models provide an acceptable fit.

	p-value
model1	0,559
model2	0,487
model3	0,430

Table 5.11 Chi-square p-values for the three models assessing the association between impulsive buying and schizotypy.

5.4 Compulsive buying

We will follow the same schedule as in the impulsive buying. Equally to the impulsive buying the questionnaire of the study comprehends five questions measuring compulsive buying. Each response was coded with values 1 to 5, with:

1- strongly agree

2- agree

3- neither agree nor disagree

4- disagree

5- strongly disagree

To simplify the problem values 1, 2 (which reflect agreement to the items statement) and 3 were recoded to zero (1), while values 4 and 5 (reflecting disagreement) were recoded to one (0) respectively. Before proceeding to modelling the recoded responses, we provide some initial statistics related to compulsive buying.

19% of our sample does not feel comfortable the days when do not buy products or does not go out for shopping; in contrast the 81% is not expressed by this reaction. On the contrary 28% respond that they buy because they just want something to buy no matter what this will be. Equally the 48% respond that they are buying things even if they will regret it later. An equal relation is getting down in the statement that: “I buy now but returning home I don’t know why I bought it”, where the 45% reacts positively while 55% disagrees that react on this way. Finally 75% agrees that when they are not in a very good mood they buy in order to feel better, while the 25% does not seem to display such behaviour.

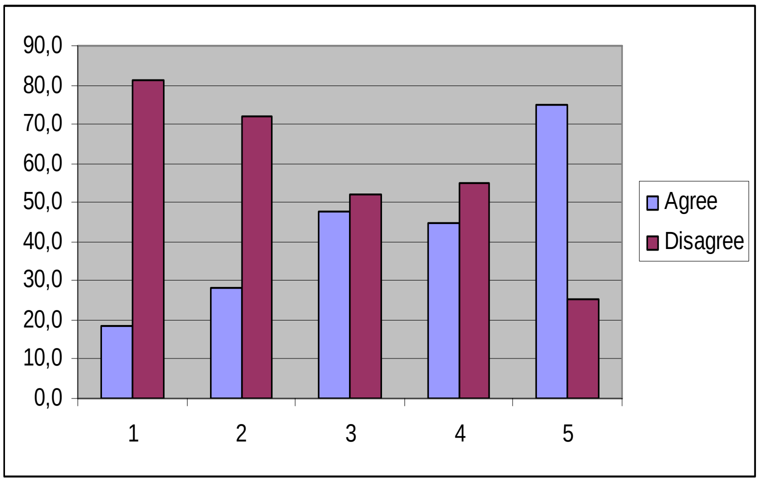


Figure 5.5 Diagram of percentages (1: Feel comfortable, 2: Buy because I want it, 3: Buy now regret it later, 4: Buy without knowing why, 5: Buy because of bad mood.)

Our next concern now is to relate compulsive buying and schizotypy. In order to examine this relationship we will construct and fit three models using WinBugs vs.1.4. In our analysis, for the models under consideration, we have generated 10000 burn-in iterations, and an additional sample of 20000 values through Gibbs sampling. Below, we describe develop in detail the theoretical framework for these models, the results of the analysis and finally related inference regarding our study data.

5.5 Models

5.5.1 Model 1

Firstly, we have constructed a model which relates compulsive buying with the nine schizotypal traits (5.8) and then is applied the model (5.9) which relates the four factors to the nine schizotypal traits. This model directly associates the observable variables while compulsive buying is indirectly related with the four latent factors. This relation is displayed by the figure below:

The model is given by the following equation:

$$comp_i \sim Binomial(n = 5, p_i^{comp})\text{, i=1,…, 167.}$$

$$\text{logit}(p_i^{comp}) = a_0 + \sum_{j=1}^{p} a_j x_{ij} + b_i \tag{5.8}$$

with $x_{ij} \sim Binomial(n_j, p_{ij})$ be the items of the schizotypal traits where n_j is the number of questions that are aggregated in its of the j schizotypal traits, j=1,…,9. In addition for the random effects we have that $b_i \sim N(0, \sigma^2)$. Finally the priors follow $a_0 \sim N(0,100)$ and $a_j \sim N(0,100)$.

In addition the nine schizotypal traits are modelled as in the previous chapter (equation 4.1).

$$x_{ij} \sim Binomial(n_j, p_{ij})$$

$$\text{logit}(p_{ij}) = a_{2j} + \sum_{k=1}^{K} \gamma_{jk} l_{jk} f_{ik} + b_{2ij} \tag{5.9}$$

The above model represents the paranoid four-factor model which was selected as the most appropriate for fitting our data in the previous chapter. For i=1,…, 167, j=1,…,9 and k=1,…,5 here we have that $b_{2ij} \sim N(0, \sigma^2)$, $f_{ik} \sim N(0,1)$. For priors we used for this model: $a_{2j} \sim N(0,100)$ and $l_{jk} \sim N(0,1)$. This model (5.9) represents the paranoid four-factor model which was selected as the most appropriate for fitting our data in the previous chapter.

Posterior summaries of parameters effects a_j (j= 0,…, 9, eq. 6.8) of the nine schizotypal traits on the log odds ratio and odds ratio of compulsive buying are presented respectively in Table 5.11 and 5.12 as estimated from the MCMC output.

Model 1				
Schizotypal Traits	**means**	**s.d**	**2.50%**	**97.50%**
Ideas of reference	0.136	0.061	0.0153	0.253
Odd beliefs or magical Thinking	0.061	0.043	-0.023	0.144
Unusual perceptual experience	0.052	0.066	-0.075	0.179
Odd speech	-0.039	0.063	-0.162	0.085
Suspiciousness	-0.094	0.061	-0.215	0.029
Constricted affect	-0.194	0.081	-0.354	-0.041
Odd behaviour	0.098	0.056	-0.012	0.209
No close friends	0.157	0.074	0.015	0.302
Social anxiety	0.019	0.058	-0.096	0.132
α_0	-1.230	0.253	-1.722	-0.724

Table 5.12 Posterior summaries of parameter effects of the nine schizotypal traits on the log odds of compulsive buying.

Model 1				
Schizotypal Traits	exp(means)	s.d.	2,5%	97,5%
Ideas of reference	1.148	0.069	1.015	1.288
Odd beliefs or magical Thinking	1.063	0.046	0.977	1.155
Unusual perceptual experience	1.056	0.069	0.928	1.197
Odd speech	0.963	0.061	0.851	1.088
Suspiciousness	0.912	0.057	0.807	1.030
Constricted affect	0.826	0.066	0.702	0.961
Odd behaviour	1.104	0.062	0.989	1.233
No close friends	1.173	0.086	1.015	1.352
Social anxiety	1.021	0.059	0.908	1.141
α_0	0.302	0.078	0.179	0.485

Table 5.13 Posterior summaries of the odds ratio of compulsive buying for each schizotypal trait.

Model 2	Factors				
Schizotypal Traits	Cogn/Perc	Negative	Disorganized	Paranoid	alpha2[j]
Ideas of reference				0.563	-0.303
Odd beliefs or magical Thinking	1.268				-0.481
Unusual perceptual experience	0.468				-1.020
Odd speech			0.799		-1.384
Suspiciousness	-0.003	0.815		1.469	-1.899
Constricted affect		0.753			-1.608
Odd behaviour			0.654		-0.678
No close friends		0.884			-1.586
Social anxiety		0.796			-0.762

Table 5.14 Factor loadings and constants for 5.9 model.

- The traits ideas of reference, odd beliefs or magical thinking, unusual perceptual thinking, odd behaviour, no close friends and finally social anxiety have positive effect on the odds of compulsive buying as we can observe from Table 5.12. An increase of one point in these scales cause an increase of 14%, 6%, 5%, 9%, 16% and 2% respectively on the odds of compulsive buying (Table 5.13).

- In addition the traits odd speech, suspiciousness and constricted affect have a negative effect on the odds of compulsive buying. These odds are decreased by 4%, 9% and 19% with an increase of one point in each scale respectively.
- Table 5.14 presents the factor loadings of the model 5.9 (the factor structure is the same as in the previous chapter). There are minor changes in the values of the factor loadings from the corresponding values of the previous chapter (Table 3.4). We can conclude that these differences are not important since the interpretation is the same as in the previous chapter.

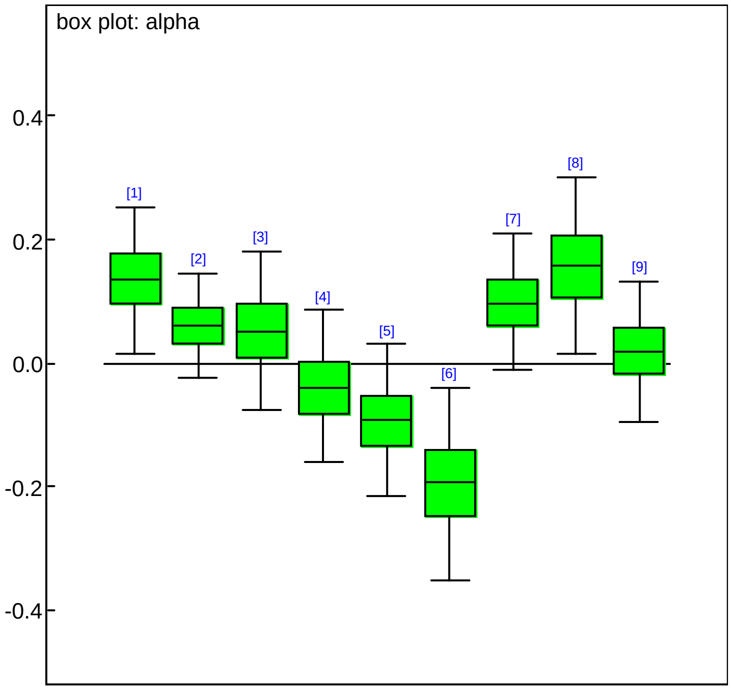


Figure 5.6 BoxPlot diagram for the parameters (schizotypal traits) of the model 5.8 ([1], [2], [3], [4], [5], [6], [7], [8], [9] correspond to ideas of reference, odd beliefs or magical thinking, unusual perceptual experience, odd speech, suspiciousness, constricted affect, odd behaviour, no close friends and social anxiety respectively).

The above figure depicts the boxplot for the parameters of the model. The plot has the same structure as in the previous chapter with the two edges presenting the 2.5% and 97.5% quantiles. (Spiegehalter et al., 2003).

From Figure 5.6 we observe that only four of the parameters have posterior distribution dispersed around zero. The effect of them on the odds of compulsive buying can not be considered as important. In contrast a_1, a_5, a_6, a_7 and a_8 are a-posteriori away from zero. As a result the traits that correspond to these parameters have a significant effect on compulsive buying.

5.5.2 Model 2

The second model we consider in this part relates compulsive buying with the four latent of schizotypy as these resulted by the Paranoid four-factor model presented in the previous chapter (5.10). In addition the four factors are also directly related to the nine schizotypal traits (5.11) as we can see below:

These relations are described by the following equation:

$$comp_i \sim Binomial(n = 5, p_i^{comp}),\ \text{i=1,…,167}$$

$$\text{logit}(p_i^{comp}) = \beta_0 + \sum_{k=1}^{4} \beta_k f_{ik} \tag{5.10}$$

with $f_{ik} \sim N(0,1)$ for k=1,…,4. The priors for this model are: $\beta_0 \sim N(0,100)$, $\beta_k \sim N(0,100)$.

The second model is expressed by the Paranoid four-factor model we have seen previously:

$$x_{ij} \sim Binomial(n_j, p_{ij})$$

$$\text{logit}(p_{ij}) = \beta_{2j} + \sum_{k=1}^{4} \gamma_{jk} l_{jk} f_{ik} + b_{2ij} \tag{5.11}$$

For the nine schizotypal traits we have that: $x_{ij} \sim Binomial(n_j, p_{ij})$, j=1,…,9. For the second model we have for the random effects that $b_{2ij} \sim N(0,\sigma^2)$. In addition we have assumed for the priors that $\beta_{2j} \sim N(0,100)$ and $l_{jk} \sim N(0,1)$. Model (5.10) is the first model we apply here and model (5.11) the second.

In the table (5.15) the posterior means of the factor loadings for the second model β_k and the constant β_0 are presented, as these are appeared after having run the model:

Model 1				
Schizotypal Traits	**means**	**s.d.**	**2.50%**	**97.50%**
Factor 1	0.218	0.177	-0.129	0.565
Factor 2	0.173	0.167	-0.153	0.506
Factor 3	0.519	0.241	0.057	1.006
Factor 4	0.433	0.737	-1.053	1.164
β_0	-0.352	0.116	-0.581	-0.127

Table 5.15 Posterior summaries of factor loadings for compulsive buying.

Model 1				
Schizotypal Traits	**means**	**s.d**	**2,5%**	**97,5%**
Factor 1	1.263	0.225	0.879	1.759
Factor 2	1.206	0.204	0.858	1.658
Factor 3	1.730	0.428	1.058	2.736
Factor 4	1.888	0.907	0.349	3.201
β_0	0.708	0.082	0.559	0.881

Table 5.16 Posterior summaries of factor loadings for the odds ratio of compulsive buying.

Model 2	Factors				
Schizotypal Traits	**Cogn/Perc**	**Negative**	**Disorganized**	**Paranoid**	β_{2j}
Ideas of reference				0.797	-0.296
Odd beliefs or magical Thinking	1.174				-0.479
Unusual perceptual experience	0.479				-1.049
Odd speech			0.702		-1.387
Suspiciousness	-0.014	-1.490		0.004	-1.783
Constricted affect		-0.649			-1.602
Odd behaviour			0.651		-0.688
No close friends		-0.654			-1.547
Social anxiety		-0.817			-0.774

Table 5.17 Factor loadings and constants for 5.11 model.

- The factor loadings here represent association between the observed variable (compulsive buying) and the latent factors. For the third and the forth factors the highest values of loadings are observed. Hence, these two factors factor are associated with increased tendency to compulsive buying. Consequently, the log odds ratio of compulsive buying loads strongly on the third and forth factor. While the same is not concluded for the first and the second. These present a lower effect on the odds ratio of compulsive buying.
- Table 5.16 presents how the four latent factors affect the odds ratio of compulsive buying. It is observed a strong effect of the odds ratio of compulsive buying on the four factors. From Table 5.15 is indicated an increase with a range between 77 and 87% for each unit increase of the factors.
- Table 5.17 presents the factor loadings of the Paranoid four- factor model. There are changes in the values of the factor loadings from the corresponding values of the previous chapter. Therefore, the interpretation must be adjusted accordingly. Equivalently to the previous chapter, the log odds ratio of odd beliefs or magical thinking load strongly on the cognitive/ perceptual factor. The effect of this factor on the log odds ratio of unusual perceptual thinking is lowest while it has a small but negative effect on suspiciousness. We observe that the log odds ratios of the correspondent traits are negatively associated to the second (negative) factor. In contrast to the previous chapter where this factor was positively associated to the corresponding traits. In addition, for the last two factors we observe that the log odds ratio of their corresponding traits have a positive effect on them. From Table 5.5 we observe that the log odds ratio of compulsive buying loads positively on the second factor (the negative factor) although this relation is the weakest, In comparison with the results for the negative factor (Table 5.17). We conclude that consuming behaviour of a person who is characterized by negative feelings (i.e. negative factor expressed by suspiciousness, constricted affect, no close friends, social anxiety) can not be characterized as compulsive.

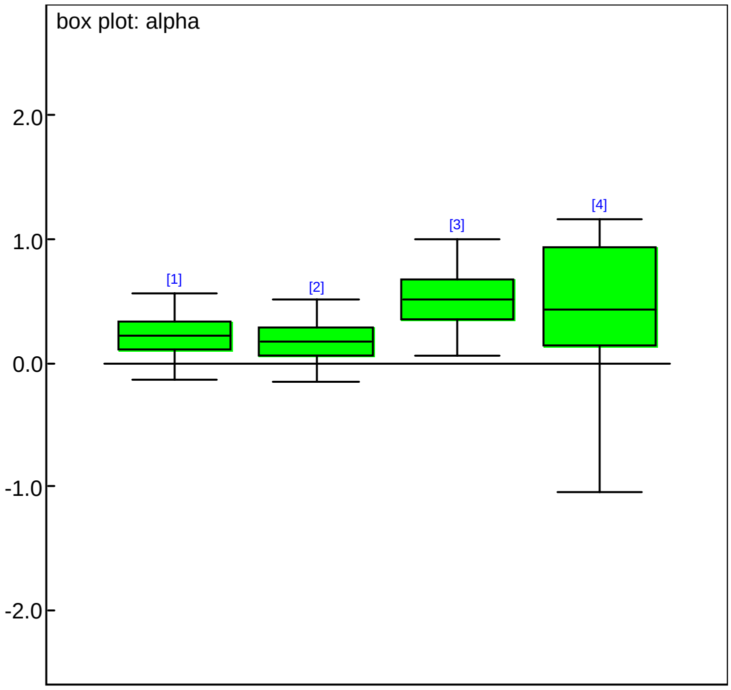


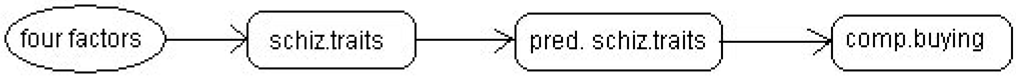
Figure 5.7 BoxPlot diagram for the parameters of the model 5.10 ([1], [2], [3], [4] correspond to factor 1, factor2, factor3 and factor 4 respectively.

Figure 5.7 displays the boxplot diagram for the four factors of the model. Here, we can conclude that none of the factors is a- posteriori distributed away from zero. As a result, the effect of the four factors factor on compulsive buying seems to be minor and cannot be considered as important.

5.5.3 Model 3

Finally, a third model based on the predictive posterior distribution of the paranoid four factor model is constructed.

Here we have constructed a model relating compulsive buying and the predictive values of the nine schizotypal. By this way we add increased variability to the first model concerning the association between the two set of variables. In this model, compulsive buying and the predicted nine schizotypal traits are connected on a direct way (5.12). This implies an indirectly relation between compulsive buying and the initially observed schizotypal traits (5.13).



The model is summarized by the following:

$$comp_i \sim Binomial(n=5, p_i^{comp})\text{, i=1,…, 167}$$

$$\text{logit}(p_i^{comp}) = a_0 + \sum_{j=1}^{9} a_j x_{ij}^{pred} + b_i \qquad (5.12)$$

x_{ij}^{pred} are the predicted schizotypal traits coming from the predictive posterior distribution and and they have the same distribution with x_{ij}: $x_{ij}^{pred} \sim Binomial(n_j, p_{ij})$, $x_{ij} \sim Binomial(n_j, p_{ij})$ j=1,…,9. In addition for the random effects we have that $b_i \sim N(0,\sigma^2)$. Finally the priors follow $a_0 \sim N(0,100)$ and $a_j \sim N(0,100)$.

The second relation as in the previous cases is described by the model:

$$x_{ij} \sim Binomial(n_j, p_{ij})$$

$$\text{logit}(p_{ij}) = a_{2j} + \sum_{k=1}^{4} \gamma_{jk} l_{jk} f_{ik} + b_{2ij} \qquad (5.13)$$

The above model represents the paranoid four-factor model which was selected as the most appropriate for fitting our data in the previous chapter. For i=1,…, 167, j=1,…,9 and k=1,…,5 here we have that the random effects follow: $b_{2ij} \sim N(0,\sigma^2)$, $f_{ik} \sim N(0,1)$. For priors we used for this model: $a_{2j} \sim N(0,100)$ and $l_{jk} \sim N(0,1)$.

In the next table are interpreted the posterior means of the estimated factor loadings for the model (5.12) and the constant a_0, as these have been appeared after our analysis:

Model 1				
Schizotypal Traits-predictive	**means**	**s.d.**	**2.50%**	**9.75%**
Ideas of reference	0.220	0.106	0.002	0.419
Odd beliefs or magical Thinking	0.076	0.072	-0.063	0.224
Unusual perceptual experience	0.070	0.139	-0.207	0.344
Odd speech	-0.073	0.111	-0.291	0.146
Suspiciousness	-0.169	0.101	-0.367	0.031
Constricted affect	-0.233	0.139	-0.505	0.044

Odd behaviour	0.169	0.107	-0.044	0.374
No close friends	0.205	0.142	-0.084	0.466
Social anxiety	0.051	0.121	-0.189	0.279
α_0	-1.806	0.427	-2.620	-0.957

Table 5.18 Posterior means of parameters effects of the predicted traits on the log odds ratio of compulsive buying.

model3				
Schizotypal Traits	**exp(means)**	**s.d**	**2,5%**	**97,5%**
Ideas of reference	1,253	0,132	1,002	1,522
Odd beliefs or magical thinking	1,082	0,079	0,939	1,251
Unusual perceptual experience	1,083	0,151	0,813	1,410
Odd speech	0,936	0,105	0,748	1,157
Suspiciousness	0,849	0,086	0,693	1,031
Constricted affect	0,799	0,111	0,604	1,044
Odd behaviour	1,192	0,127	0,957	1,453
No close friends	1,240	0,175	0,919	1,593
Social anxiety	1,060	0,128	0,827	1,322
α_0	0,180	0,081	0,073	0,384

Table 5.19 Posterior summaries of parameters effects of the predicted traits on odds ratio of compulsive buying.

model4	**Factors**				
Schizotypal Traits	**Cogn/Perc**	**Negative**	**Disorganized**	**Paranoid**	α_{2j}
Ideas of reference				0.571	-0.295
Odd beliefs or magical Thinking	1.286				-0.487
Unusual perceptual experience	0.464				-1.052
Odd speech			0.811		-1.392
Suspiciousness	-0.017	0.808		1.480	-1.778
Constricted affect		0.755			-1.599
Odd behaviour			0.669		-0.681
No close friends		0.886			-1.548
Social anxiety		0.799			-0.777

Table 5.20 Factor loadings and constants for 5.13 model.

- The traits ideas of reference, odd beliefs or magical thinking, unusual perceptual thinking, odd behaviour, no close friends and finally social anxiety have positive effect on the odds of compulsive buying as we can observe from Table 5.18 (the same is observed from Table 5.19 where these traits present values larger to one). An increase of one point on these scales cause an increase of 22%, 8%, 7% , 17%, 21% and 5% respectively on the odds of compulsive buying.

- Moreover, the predicted odd speech, suspiciousness and constricted affect have a negative effect on the odds of compulsive buying. These odds are decreased by 7%, 17% and 23% with an increase of one point in each scale respectively.
- Table 5.20 presents the factor loadings of the model 5.13 (the factor structure is the same as in the previous chapter). There are minor changes in the values of the factor loadings from the corresponding values in the previous chapter (Table 4.4). We can conclude that these differences are minor since the interpretation is the same as in the previous chapter.

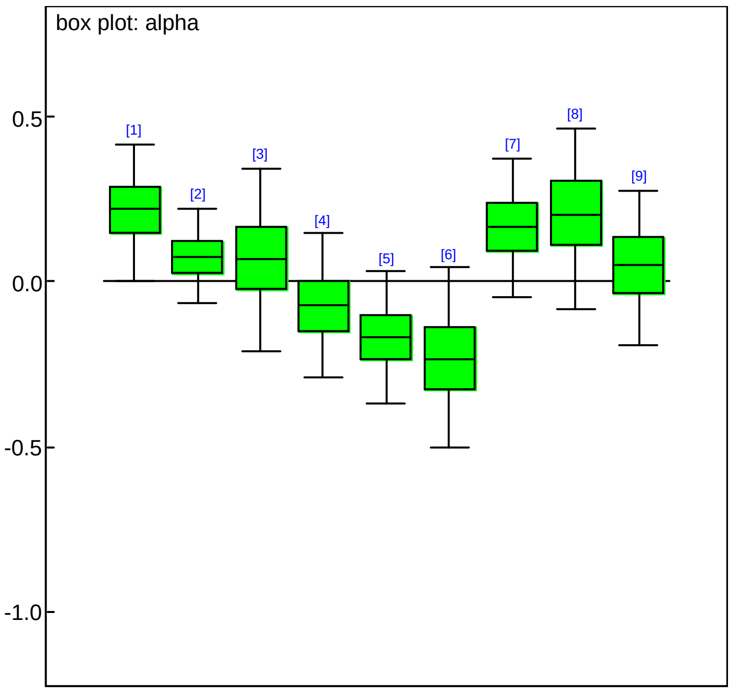


Figure 5.8 BoxPlot diagram for the parameters of the model 5.12 ([1], [2], [3], [4], [5], [6], [7], [8], [9] correspond to ideas of reference, odd beliefs or magical thinking, unusual perceptual experience, odd speech, suspiciousness, constricted affect, odd behaviour, no close friends and social anxiety respectively).

Figure 5.8 depicts the Boxplot diagram for the parameters of the model 5.12. We observe that four of the parameters have posterior distribution dispersed around zero. The effect of them on the odds of compulsive buying can not be considered as important. In contrast, a_1, a_5, a_6, a_7 and a_8 are a- posteriori away from zero. As a result the traits that correspond to these parameters have a significant effect on compulsive buying.

5.6 Models Comparison of the compulsive buying- schizotypy

In the previous section 5.5 three models were presented able to describe the relation between compulsive buying and schizotypy.

The three models analyzed above are compared here using the information criteria AIC, BIC. As the number of free parameters we consider, the number of estimated factor loadings. In all the cases the most appropriate model is this one which seems to have the smallest value of the information criteria. After the calculations via WinBugs we come up with the results presented in the Table 5.20.

	AIC	BIC	deviance
model1	4266	4294	4852
model2	4046	4074	4856
model3	3998	4026	4841

Table 5.21 Information Criteria for the three models assessing the association between compulsive buying and sschizotypy.

It is easily observable from the Table 5.20 that here in the case of compulsive buying the model which is proved to be the best one, is the third model (model 5.12, see section 5.5.3). This is based for the calculations on the predictive posterior distribution of the latent factor model. It displays the smallest value of AIC and BIC information criteria. So, we can say that the replicate schizotypal traits have the greater influence to the probability of positive response in compulsive buying.

Relatively to the chi-square statistic test in the case of compulsive buying is observed the same as in the case of impulsive buying. Although the third model is chosen as the best model to fit our data according to AIC/ BIC.

According to chi-square statistic test (Table 5.22) the three models have an acceptable fit while the best fit is provided by the first model.

	p-value
model1	0,501
model2	0,476
model3	0,372

Table 5.22 Chi-square p-values for the three models assessing the association between compulsive buying and schizotypy.

5.7 Conclusion

In this chapter our concern was to relate consumer's behaviour which was expressed by impulsive and compulsive buying to schizotypy. In order to examine this relationship we constructed and fitted three models. In both cases it was easily concluded that the most appropriate model to fit our data was the model which was based on the predictive distribution. It was observed that the replicate schizotypal traits have the greater influence to the probability of positive response in both impulsive and compulsive buying.

Something that has to be mentioned here is that in both cases-of impulsive and compulsive buying- there was not observed a strong relation between consumer's behavior and schizotypy. We concluded that, because the traits related to schizotypy cause changes of small percentages on impulsive and compulsive buying. Only the trait no close friends is of higher effect on impulsive buying since an increase of one point in its scale will cause an increase of 46% on the odds of impulsive buying.

Thus, if someone is used to impulsive or compulsive buying this does not mean that he is characterized by schizotypy. In contrast we could say that this relation seems to be weak since the majority of schizotypal traits affect weakly the two consuming behaviors. As a result a person who is characterized by the nine schizotypal traits or even some of them this can not ensure us that there is an impulsive or compulsive consuming behavior.

CHAPTER 6
FURTHER DISCUSSION AND RESEARCH

6.1 Discussion and conclusion

6.1.1 Introduction

In this thesis we have examined the association between impulsive- compulsive buying and schizotypy and the nine schizotypal traits: ideas of reference, odd beliefs or magical thinking, unusual perceptual experience, suspiciousness, social anxiety, no close friends, constricted affect, odd behaviour and odd speech. These schizotypal traits aggregate all the information available coming from the 74 items of the schizotypal personality questionnaire (SPQ). Since the SPQ expresses the schizotypal personality disorder, our goal was to examine whether such a disorder is connected to consumer's specific behavior.

6.1.2 The dimension of schizotypy

The Bayesian approach has been adopted for the analysis of schizotypy in this thesis. To facilitate estimation MCMC algorithms were used with WinBugs software. Originally only one or two dimensions (or factors) of SPQ were considered in psychiatric research. Recently more complex structures have been developed in literature for explaining schizotypal traits.

Raine et al. (1994) proposed that the nine traits of the SPQ must be analyzed using three dimensions. His model was named the Disorganized three factor model. However, recent researchers did not adopt his point of view (Bergman, 1966; Stefanis et al., 2004). Stefanis et al. (2004) proposed the Paranoid four factor model where the nine factors analyzed in four dimensions. Finally Fogelson et al. (1999) introduced the five factor model which adopts the idea that the traits are analyzed in five dimensions.

In our analysis, all the above five models were implemented using the Binomial response distribution while the previous researchers have used the normal distribution. Three different information criteria were used to decide which model is more appropriate. According to our results we have concluded that the Paranoid four factor model assures us the best fit since it presents the smallest value of AIC/ BIC.

In other words, we have concluded that the nine schizotypal traits are best described by the Paranoid four factor model. The factors as were proposed by Stefanis et al. (2004) are known as: the cognitive/ perceptual, the negative, the disorganized and finally the paranoid factor. Additionally all factors had an important contribution to our model since the posterior distribution of the loadings was away from zero.

6.1.3 Association of schizotypy and impulsive buying

Since we have concluded to the best fitted factor model, our next goal was to relate SPQ with impulsive and compulsive buying behaviour. This scale was formed from five responses in each case. We had aggregated the information available from the questions in one separate scale.

In the first case this one of impulsive buying, we have applied three models in order to associate impulsive buying with the schizotypy that is the nine schizotypal traits. In fact, our aim was to link impulsive buying with the above schizotypy factor model.

Three alternative models have been considered. Firstly, we have associated it with the nine schizotypal traits while in the second case we related directly the data of impulsive buying with the four factors. Finally in the third model we have constructed a model which relates impulsive buying with the predictive values of the nine schizotypal traits.

After having completed our analysis we propose one model which provides the best description of our data according to AIC/ BIC. The third model which includes the predictive schizotypal values was selected in this case. From the results we have seen only some of them influence impulsive buying.

To be more specific, the predicted traits ideas of reference, unusual perceptual thinking, odd behaviour and no close friends have positive effect on the odds of impulsive buying. They can cause an increase of 18%, 2%, 5% and 46% respectively on the odds of impulsive buying by an increase of one point on their scales. The trait no close friends seem to have the highest effect on impulsive buying as it causes the highest change on its odds. The rest of the traits cause a low decrease on these odds. These are the predicted odd beliefs or magical thinking, odd speech, suspiciousness, constricted affect and social anxiety have a negative effect on the odds of impulsive buying which can decrease by 5%, 7%, 13%, 1% and 17% the correspondent odd of impulsive buying with an increase of one point in each scale respectively.

As it is observed from the results, the trait no close friends is more closely related to impulsive buying since it can cause the highest percentage of positive change. While the trait social anxiety cause the highest negative change on impulsive buying.

6.1.4 Association of schizotypy and compulsive buying

The same analysis as for impulsive buying was also performed for compulsive buying. Similarly as in the case of impulsive the third model was selected (which includes the predictive schizotypal values) as the best one according to AIC/ BIC.

Ideas of reference, odd beliefs (or magical thinking), unusual perceptual thinking, odd behaviour, no close friends and finally social anxiety have a positive effect on the odds of compulsive buying. They cause an increase of 22%, 8%, 7%, 17%, 21% and 5% respectively on the odds of compulsive buying by an increase of one point on their scales. The predicted odd speech, suspiciousness and constricted affect have a negative effect on the odds of compulsive buying. These odds decrease by 7%, 17% and 23% with an increase of one point in each scale respectively.

Equivalently to the results of impulsive buying, the trait no close friends is strongly associated with compulsive buying since it can cause the highest percentage of positive change. On the contrary, social anxiety has a weak influence on compulsive buying. Finally the trait constricted affect causes the highest percentage of compulsive buying decrease.

6.1.5 Conclusion

A general conclusion here for the two cases of buying is that no strong connection of buying behavior and schizotypy is observed. Therefore, even if a person responds positively or not to the nine schizotypal traits or even some of them this can not ensure us that will be characterized by the two consuming behaviors. In contrast, it does not seem to exist a strong relation between schizotypy and consuming behavior in both cases.

Thus, a schizotypal person is not strongly possible to display an impulsive or a compulsive consuming behavior. In contrary, only in cases that this person reacts positively to some of the traits expressing schizotypy may display such a consuming behavior.

6.2 Further research

Further methodological approaches can be facilitated to analyze data with similar structure. In this section we briefly describe some of them.

These data used in this thesis were collected in a general questionnaire including the Schizotypal personality questionnaire (SPQ) and items measuring impulsive and compulsive behaviour of individuals (see Iliopoulou, 2004).

The responses to the 74 SPQ items were coded using the zero- one scale (0, 1). These 74 items were assumed to follow a Bernoulli distribution:

$$w_{ij} \sim Bernoulli(p_{ij}), \tag{6.1}$$

where p_{ji} represents the probability of positive response or success of i subject on j item (j=1,…, 9, i=1,…, 74).

The results were summed and on this way we formed the nine schizotypal traits. These nine traits were following binomial distribution:

$$x_{ij} \sim Binomial(\pi_{ij}, n_j), \text{ i=1,…,74 and j=1,…, 9} \tag{6.2}$$

where π_{ij} is the probability of success of i subject on j SPQ sub- scale and n_j is the number of individual Bernoulli items included in the j-th schizotypal trait.

In this thesis we have used the logit link function resulting in the following model equation:

$$\text{logit}(\pi(y)) = \log\frac{\pi_i(y)}{1-\pi_i(y)} = a_{i0} + a_{i1}y_{i1} + ... + a_{iq}y_{iq} + \varepsilon_i \ . \tag{6.3}$$

6.2.1 Link functions

6.2.1.1 Probit function

Alternatively we may use the probit transformation $\Phi^{-1}(\pi(y))$ as link function, where Φ is the standard normal cumulative distribution function. In the case of this transformation the general model becomes:

$$\Phi^{-1}(\pi(y)) = a_{i0} + a_{i1}y_{i1} + ... + a_{iq}y_{iq} + \varepsilon_i \,. \tag{6.4}$$

As a result and according to the above general model, the model (4.1) that was applied in our analysis now becomes:

$$\Phi^{-1}(\pi(f)) = a_j + \sum_{k=1}^{K} l_{ij} f_{ik} + b_{ij} \,. \tag{6.5}$$

for K=1, …, 5 representing the five possible factors and their associated model(e.g. if k=3 then we have the three facor model), j=1, …, 9 representing the nine schizotypal traits and i=1, …, 167 representing the observations where:
$b_{ij} \sim N(0,1)$, $a_j \sim N(0,100)$ and $f_{ik} \sim N(0,1)$.

6.2.1.2 Loglog function

In this case the link function is the log-log function (Laaksonen, 2006). Using this transformation the general model becomes:

$$-\log(-\log(\pi(y))) = a_{i0} + a_{i1}y_{i1} + .. + a_{iq}y_{iq} + \varepsilon_i \tag{6.6}$$

The model 5.1 will be:

$$-\log(-\log(\pi(f))) = a_j + \sum_{k=1}^{K} l_{ij} f_{ik} + b_{ij} \tag{6.7}$$

for $b_{ij} \sim N(0,1)$, $a_j \sim N(0,100)$ and $f_{ij} \sim N(0,1)$.

6.2.1.3 Complementary Loglog function

In this case the link function is based on the previous the log-log function. Using this transformation the general model becomes:

$$\log(-\log(\pi(y))) = a_{i0} + a_{i1}y_{i1} + .. + a_{iq}y_{iq} + \varepsilon_i \,. \tag{6.8}$$

The model 5.1 becomes:

$$\log(-\log(\pi(f))) = a_j + \sum_{k=1}^{K} l_{ij} f_{ik} + b_{ij} \,, \tag{6.9}$$

for $b_{ij} \sim N(0,1)$, $a_j \sim N(0,100)$ and $f_{ij} \sim N(0,1)$.

6.2.1.4 Suggestion

In the previous section (**6.2.1**) we mention three different link functions. It will be interesting to fit all the above models and examine which link function might be describing the data better. However, in our analysis we chose to use the logit link function because according to previous researchers it is the more conventional link function in survey estimation as far as a categorical variable including response indicator have been applied.

Rarely the other links have been used, this being probit according to Laaksonen (2006). She also added that: "*the choice of the link function is not the most important issue in survey estimation but still a user could also look forward to some other link functions*".

APPENDIX A

Descriptive characteristics of the sample- Frequency Tables

University		
	Frequency	Percent
TEI	72	43,1
AEI	95	56,9
Total	167	100

Table A.1 Frequency Table for university.

Study level		
	Frequency	Percent
Bsc	152	91
Msc	15	9
Total	167	100

Table A.2 Frequency Table for Study level.

Age		
	Frequency	Percent
18-21	90	53,9
22-25	64	38,3
26-29	11	6,6
30+	2	1,2
Total	167	100

Table A.3 Frequency Table for age.

Gender		
	Frequency	Percent
Male	74	44,3
Female	93	55,7
Total	167	100

Table A.4 Frequency Table for gender.

Economic Status		
	Frequency	Percent
Low	9	5,4
Median	151	90,4
High	7	4,2
Total	167	100

Table A.5 Frequency Table for Economic Status.

Independence		
	Frequency	Percent
Yes	137	82
No	21	12,6
Else	9	5,4
Total	167	100

Table A.6 Frequency Table for financial independence.

APPENDIX B
Factor loadings of five factor models

Model 1

model1	Factor1	alpha[j]
Ideas of reference	0,708	-0,285
Odd beliefs or magical thinking	0,632	-0,405
Unusual perceptual experience	0,801	-1,046
Odd speech	0,879	-1,367
Suspiciousness	1,425	-1,651
Constricted affect	0,532	-1,533
Odd behaviour	0,749	-0,659
No close friends	0,619	-1,495
Social anxiety	0,897	-0,747

Table B.1 Factor loadings for the one factor model.

Model 2

model2	Factors		
Schizotypal Traits	**Positive**	**Negative**	**alpha[j]**
Ideas of reference	0,747		-0,297
Odd beliefs or magical thinking	0,473		-0,405
Unusual perceptual experience	0,954		-1,085
Odd speech	0,902		-1,379
Suspiciousness	1,133	0,732	-1,682
Constricted affect		0,732	-1,575
Odd behaviour		0,579	-0,649
No close friends		0,929	-1,571
Social anxiety	0,737	0,398	-0,748

Table B.2 Factor loadings for the Kendler's two- factor model.

Model 3

model3	Factors			
Schizotypal Traits	Cogn/Perc	Interpersonal	Disorganized	alpha[j]
Ideas of reference	0,034			-0,293
Odd beliefs or magical thinking	-1,161			-0,471
Unusual perceptual experience	-0,493			-1,037
Odd speech			-0,742	-1,375
Suspiciousness	-0,032	1,450		-1,714
Constricted affect		0,644		-1,565
Odd behaviour			-0,617	-0,675
No close friends		0,667		-1,517
Social anxiety		0,822		-0,744

Table B.3 Factor loadings for the Disorganized three- factor model.

Model 5

model5	Factors					
Schizotypal Traits	**Paranoid**	**Positive**	**Schizoid**	**Avoidant**	**Disorganized**	**alpha[j]**
Ideas of reference	0,319	0,210		0,558		-0,308
Odd beliefs or magical thinking		1,278				-0,473
Unusual perceptual experience		0,521				-1,006
Odd speech			0,509			-1,286
Suspiciousness	1,032				1,335	-1,823
Constricted affect			0,641		0,266	-1,563
Odd behaviour					0,625	-0,648
No close friends			0,937			-1,563
Social anxiety				1,006		-0,778

Table B.4 Factor loadings for the Fogelson's five- factor model.

APPENDIX C

Characteristics of impulsive and compulsive buying.

1. Impulsive buying

Q1		
	Frequency	Percent
Agree	79	47,3
Disagree	98	52,7
Total	167	100,0

Table C.1 Just do it.

Q2		
	Frequency	Percent
Agree	97	58,1
Disagree	70	41,9
Total	167	100,0

Table C.2 Buy without thinking.

Q3		
	Frequency	Percent
Agree	132	79,0
Disagree	35	21,0
Total	167	100,0

Table C.3 Buy now, think of it later.

Q4		
	Frequency	Percent
Agree	58	34,7
Disagree	109	65,3
Total	167	100,0

Table C.4 React carelessly when buying.

Q5		
	Frequency	Percent
Agree	41	24,6
Disagree	126	75,4
Total	167	100,0

Table C.5 Buy sth that want it immediately when see it.

2. Compulsive Buying

Q1		
	Frequency	Percent
Agree	136	21,4
Disagree	31	18,6
Total	167	100,0

Table C.6 Do not feel comfortable without buying.

Q2		
	Frequency	Percent
Agree	120	71,9
Disagree	47	28,1
Total	167	100,0

Table C.7 Buy because I want it.

Q3		
	Frequency	Percent
Agree	87	52,1
Disagree	80	47,9
Total	167	100,0

Table C.8 Buy now, regret it later.

Q4		
	Frequency	Percent
Agree	92	55,1
Disagree	75	44,9
Total	167	100,0

Table C.9 Buy without knowing why.

Q5		
	Frequency	Percent
Agree	42	25,1
Disagree	125	74,9
Total	167	100,0

Table C.10 Buy because of bad mood.

APPENDIX D

Codes of chosen models

1. Four-Factor Paranoid Model

```
model;
{
  for (i in 1:N){
 for(j in 1:9){
  x[i,j]~dbin(p[i,j],n[j])

####model (5.1)
  logit(p[i,j])<-alpha[j]+l[1,j]*f[i,1]+l[2,j]*f[i,2]+l[3,j]*f[i,3]+l[4,j]*f[i,4]+b[i,j]
  b[i,j]~dnorm(0.0,tau)
  f[i,j]~dnorm(0,1)

####log- likelihood function
  loglikel[i,j]<-logfact(n[j]) - logfact(x[i,j]) - logfact(n[j]-
x[i,j])+x[i,j]*log(p[i,j])+(n[j]-x[i,j])*log(1-p[i,j])
 }
}
####priors
  for(j in 1:9){
   alpha[j]~dnorm(0,0.01)
  }
  l[1,1]<-0
  l[1,2]~dnorm(0,1)I(0,)
  l[1,3]~dnorm(0,1)
  l[1,4]<-0
  l[1,5]~dnorm(0,1)
  l[1,6]<-0
  l[1,7]<-0
  l[1,8]<-0
  l[1,9]<-0
  l[2,1]<-0
  l[2,2]<-0
  l[2,3]<-0
  l[2,4]<-0
  l[2,5]~dnorm(0,1)
  l[2,6]~dnorm(0,1)
  l[2,7]<-0
  l[2,8]~dnorm(0,1)
  l[2,9]~dnorm(0,1)
  l[3,1]<-0
  l[3,2]<-0
  l[3,3]<-0
  l[3,4]~dnorm(0,1)I(0,)
```

```
l[3,5]<-0
l[3,6]<-0
l[3,7]~dnorm(0,1)
l[3,8]<-0
l[3,9]<-0
l[4,1]~dnorm(0,1)I(0,)
l[4,2]<-0
l[4,3]<-0
l[4,4]<-0
l[4,5]~dnorm(0,1)
l[4,6]<-0
l[4,7]<-0
l[4,8]<-0
l[4,9]<-0
tau~dgamma(1,1)
L1<-sum(loglikel[,])
BIC<- -2*L1+11*log(N)
AIC<- -2*L1+ 11*2

}
```

2. Impulsive model

2.1 Model 1

```
model;
{
  for (i in 1:N){
    imp[i]~dbin(p[i],5)
####model (6.1)
     logit(p[i])<-alpha0+inprod(alpha[],x[i,])+b[i]
     b[i]~dnorm(0.0,tau)
     for(j in 1:9){
     x[i,j]~dbin(p2[i,j],n[j])
####model (6.2)
     logit(p2[i,j])<-alpha2[j]+l[1,j]*f[i,1]+l[2,j]*f[i,2]+l[3,j]*f[i,3]+l[4,j]*f[i,4]+b2[i,j]
     b2[i,j]~dnorm(0.0,tau)
     f[i,j]~dnorm(0,1)
####log-likelihood function
     loglikel[i,j]<-logfact(5)-logfact(imp[i])-logfact(5-imp[i])+imp[i]*log(p[i])+(5-
imp[i])*log(1-p[i])
    }
  }
####priors
  tau~dgamma(1,1)
  alpha0~dnorm(0,0.01)
  e.alpha0<-exp(alpha0)
  for(j in 1:9){
   e.alpha[j]<-exp(alpha[j])
   alpha[j]~dnorm(0,0.01)
   alpha2[j]~dnorm(0,0.01)
  }
  l[1,1]<-0
  l[1,2]~dnorm(0,1)I(0,)
  l[1,3]~dnorm(0,1)
  l[1,4]<-0
  l[1,5]~dnorm(0,1)
  l[1,6]<-0
  l[1,7]<-0
  l[1,8]<-0
  l[1,9]<-0
  l[2,1]<-0
  l[2,2]<-0
  l[2,3]<-0
  l[2,4]<-0
  l[2,5]~dnorm(0,1)
  l[2,6]~dnorm(0,1)
  l[2,7]<-0
  l[2,8]~dnorm(0,1)
  l[2,9]~dnorm(0,1)
  l[3,1]<-0
```

```
  l[3,2]<-0
  l[3,3]<-0
  l[3,4]~dnorm(0,1)I(0,)
  l[3,5]<-0
  l[3,6]<-0
  l[3,7]~dnorm(0,1)
  l[3,8]<-0
  l[3,9]<-0
  l[4,1]~dnorm(0,1)I(0,)
  l[4,2]<-0
  l[4,3]<-0
  l[4,4]<-0
  l[4,5]~dnorm(0,1)
  l[4,6]<-0
  l[4,7]<-0
  l[4,8]<-0
  l[4,9]<-0
  s2<-1/tau
  L1<-sum(loglikel[,])
  BIC<- -2*L1+9*log(N)
  AIC<- -2*L1+ 9*2
 }
```

2.2 Model 2

```
model;
{
  for (i in 1:N){
  imp[i]~dbin(p[i],5)
####model (6.3)
  logit(p[i])<-alpha0+alpha[1]*f[i,1]+alpha[2]*f[i,2]+alpha[3]*f[i,3]+alpha[4]*f[i,4]
  for(j in 1:9){
  f[i,j]~dnorm(0,1)
  x[i,j]~dbin(p2[i,j],n[j])
####model (6.4)
  logit(p2[i,j])<-alpha2[j]+l[1,j]*f[i,1]+l[2,j]*f[i,2]+l[3,j]*f[i,3]+l[4,j]*f[i,4]+b2[i,j]
  b2[i,j]~dnorm(0.0,tau)
####log-likelihood function
  loglikel[i,j]<-logfact(5)-logfact(p[i])-logfact(5-p[i])+imp[i]*log(p[i])+(5-
imp[i])*log(1-p[i])
  }
 }
####priors
 tau~dgamma(1,1)
  alpha0~dnorm(0,0.01)
  e.alpha0<-exp(alpha0)
  for(k in 1:4){
   e.alpha[k]<-exp(alpha[k])
   alpha[k]~dnorm(0,0.01)
  }
```

```
 for(j in 1:9){
  alpha2[j]~dnorm(0,0.01)
 }

 l[1,1]<-0
 l[1,2]~dnorm(0,1)I(0,)
 l[1,3]~dnorm(0,1)
 l[1,4]<-0
 l[1,5]~dnorm(0,1)
 l[1,6]<-0
 l[1,7]<-0
 l[1,8]<-0
 l[1,9]<-0
 l[2,1]<-0
 l[2,2]<-0
 l[2,3]<-0
 l[2,4]<-0
 l[2,5]~dnorm(0,1)
 l[2,6]~dnorm(0,1)
 l[2,7]<-0
 l[2,8]~dnorm(0,1)
 l[2,9]~dnorm(0,1)
 l[3,1]<-0
 l[3,2]<-0
 l[3,3]<-0
 l[3,4]~dnorm(0,1)I(0,)
 l[3,5]<-0
 l[3,6]<-0
 l[3,7]~dnorm(0,1)
 l[3,8]<-0
 l[3,9]<-0
 l[4,1]~dnorm(0,1)I(0,)
 l[4,2]<-0
 l[4,3]<-0
 l[4,4]<-0
 l[4,5]~dnorm(0,1)
 l[4,6]<-0
 l[4,7]<-0
 l[4,8]<-0
 l[4,9]<-0
 s2<-1/tau
 L1<-sum(loglikel[,])
 BIC<- -2*L1+9*log(N)
 AIC<- -2*L1+ 9*2
}
```

2.3 Model 3

```
model;
{
  for (i in 1:N){
    imp[i]~dbin(p[i],5)
####model (6.6)
    logit(p[i])<-alpha0+inprod(alpha[],x.rep[i,])+b[i]
    b[i]~dnorm(0.0,tau)
    for(j in 1:9){
     x.rep[i,j]~dbin(p2[i,j],n[j])
     x[i,j]~dbin(p2[i,j],n[j])
####model (6.7)
     logit(p2[i,j])<-alpha2[j]+l[1,j]*f[i,1]+l[2,j]*f[i,2]+l[3,j]*f[i,3]+b2[i,j]
     b2[i,j]~dnorm(0.0,tau)
     f[i,j]~dnorm(0,1)
####log- likelihood function
     loglikel[i,j]<-logfact(5)-logfact(imp[i])-logfact(5-imp[i])+imp[i]*log(p[i])+(5-
imp[i])*log(1-p[i])
    }
  }
####priors
 tau~dgamma(1,1)
   alpha0~dnorm(0,0.01)
  e.alpha0<-exp(alpha0)
  for(j in 1:9){
   e.alpha[j]<-exp(alpha[j])
   alpha[j]~dnorm(0,0.01)
   alpha2[j]~dnorm(0,0.01)
  }
  l[1,1]<-0
  l[1,2]~dnorm(0,1)I(0,)
  l[1,3]~dnorm(0,1)
  l[1,4]<-0
  l[1,5]~dnorm(0,1)
  l[1,6]<-0
  l[1,7]<-0
  l[1,8]<-0
  l[1,9]<-0
  l[2,1]<-0
  l[2,2]<-0
  l[2,3]<-0
  l[2,4]<-0
  l[2,5]~dnorm(0,1)
  l[2,6]~dnorm(0,1)
  l[2,7]<-0
  l[2,8]~dnorm(0,1)
  l[2,9]~dnorm(0,1)
  l[3,1]<-0
  l[3,2]<-0
  l[3,3]<-0
```

```
l[3,4]~dnorm(0,1)I(0,)
l[3,5]<-0
l[3,6]<-0
l[3,7]~dnorm(0,1)
l[3,8]<-0
l[3,9]<-0
l[4,1]~dnorm(0,1)I(0,)
l[4,2]<-0
l[4,3]<-0
l[4,4]<-0
l[4,5]~dnorm(0,1)
l[4,6]<-0
l[4,7]<-0
l[4,8]<-0
l[4,9]<-0
s2<-1/tau
L1<-sum(loglikel[,])
BIC<- -2*L1+9*log(N)
AIC<- -2*L1+ 9*2
}
```

APPENDIX E

Markov Chain Monte Carlo (MCMC) Methods

Monte Carlo Integration

Monte Carlo method was originally named by Ulam (1951). This method is based on the drawing of random samples, which have some useful properties, for solving a problem. It is of great importance because it enables us to simplify complicated calculations. Nicolas Metropolis had also an important contribution to the development of such methods.

Monte Carlo integration is a method for estimating complicated integrals of random samples (drawn from a target distribution) by calculating their expectations. Let us consider the quantity:

$$\theta = \int \mu(x)\, f(x) dx \ .$$

We will approximate this integral by sampling. Suppose we have a sample of $x = (X_1, ..., X_N)$ from the above density $f(x)$, then the estimate of θ will be:

$$\hat{\theta} \approx \frac{1}{\mathrm{N}} \sum_{i=1}^{\mathrm{N}} \mu(X_i)$$

Hence the population expectation of $\mu(x)$ can be estimated by the corresponding sample mean. Since $\hat{\theta}$ results from a simulation process we can set N large (the bigger the better) and hence $\hat{\theta}$ will asymptotically approximate θ. When the generated observations are independent then we can increase the sample size to get more accurate estimations. It is not necessary to have independent realizations. The samples can be drawn by any process we desire (Gilks, Richardson and Spiegelhalter, 1996 p.4). Having in mind the above, we can conclude that the application of Monte Carlo integration is relatively simple since we only have to generate samples and then use point estimates for the quantities of interest.

Markov Chain

Let us now consider a sequence of discrete random variables $\left\{\theta^{(1)},\theta^{(2)},...,\theta^{(t)}\right\}$ with the property that the distribution of $\theta^{(t+1)}$ conditioning on $\left\{\theta^{(0)},\theta^{(1)},...,\theta^{(t)}\right\}$ depends only on the previous value of $\theta^{(t)}$ and not on the values of $\left\{\theta^{(0)},\theta^{(1)},...,\theta^{(t-1)}\right\}$:

$$f\left(\theta^{(t+1)} \mid \theta^{(t)},\theta^{(t-1)}...,\theta^{(1)}\right) = f\left(\theta^{(t+1)} \mid \theta^{(t)}\right) \ ,$$

where $f\left(\theta^{(t+1)} \mid \theta^{(t)}\right)$ is independent of t.

Such a stochastic process $\left\{\theta^{(t)} : t = 0,1,...\right\}$ is called Markov Chain

MCMC Algorithms

Metropolis –Hasting Algorithm

Metropolis et al (1953) introduced the Metropolis algorithm described in this section.

As it was proposed, in order to generate $\theta^{(t+1)}$ having already observed $\theta^{(t)}$ we have to:

- Draw θ^{*} from a proposal distribution $q\left(\theta^{*} \mid \theta^{(t)}\right)$, which is symmetric:

$$q\left(\theta^{*} \mid \theta^{(t)}\right) = q\left(\theta^{(t)} \mid \theta^{*}\right)$$

- Calculate the acceptance probability:

$$a\left(\theta^{*},\theta^{(t)}\right) = \min\left(1,\frac{f\left(\theta^{*} \mid y\right)}{f\left(\theta^{(t)} \mid y\right)}\right)$$

- Accept the proposed more from θ to θ^{*} with probability a.

Generate u~ U (0, 1). If $u < a$ then accept and $\theta^{(t+1)} = \theta^*$, otherwise reject the more and set $\theta^{(t+1)} = \theta^{(t)}$

And then repeat the above steps until an accepted sample from the target distribution is obtained.

In Metropolis –Hasting algorithm we do not have the restriction of using a symmetrical proposal distribution. Hence the algorithm is now given by the following steps.

- Draw θ^* from a distribution $q\left(\theta^* \mid \theta^{(t)}\right)$
- The acceptance probability now is:

$$a\left(\theta^*, \theta^{(t)}\right) = \min\left(1, \frac{f\left(\theta^* \mid y\right) q\left(\theta^{(t)} \mid \theta^*\right)}{f\left(\theta^{(t)} \mid y\right) q\left(\theta^* \mid \theta^{(t)}\right)}\right)$$

- Accept the proposed more from θ to θ^* with probability a.

Generate u~ U (0,1). If $u < a$ then accept and $\theta^{(t+1)} = \theta^*$, otherwise reject the more and set $\theta^{(t+1)} = \theta^{(t)}$.

The Gibbs Sampler

The Gibbs sampler is a special case of Metropolis Hasting algorithm. Here the proposal distribution is the full conditional distribution. For the i-th component of a vector θ is generated from $f_i(\theta_i \mid \theta_{-i}, y)$. θ_{-i} represents the vector θ excluding the i-th component: $\theta_{-i} = (\theta_1, ..., \theta_{i-1}, \theta_{i+1}, ..., \theta_k)$. Suppose we have a vector of k random variables $\theta = \left(\theta_1, \theta_2, ..., \theta_k\right)$ and a set of initial values $\left(\theta_1^{(0)}, \theta_2^{(0)}, ..., \theta_k^{(0)}\right)$. Then

- we generate

$$\begin{array}{lll}
\theta_1^{(1)} & \text{from} & f_1\left(\theta_1 \mid \theta_2^{(0)}, \theta_3^{(0)}, ..., \theta_k^{(0)}, y\right) \\
\theta_2^{(1)} & \text{from} & f_2\left(\theta_2 \mid \theta_1^{(1)}, \theta_3^{(0)}, ..., \theta_k^{(0)}, y\right) \\
\theta_3^{(1)} & \text{from} & f_3\left(\theta_3 \mid \theta_1^{(1)}, \theta_2^{(1)}, ..., \theta_k^{(0)}, y\right) \\
\vdots & & \quad\vdots \qquad \vdots \qquad \vdots \\
\theta_k^{(1)} & \text{from} & f_k\left(\theta_k \mid \theta_1^{(1)}, \theta_2^{(1)}, ..., \theta_{k-1}^{(1)}, y\right)
\end{array}$$

Generally we sample $\theta_j^{(t+1)}$ from:

$$\theta_j^{(t+1)} \sim f_j\left(\theta_j \mid \theta_1^{(t+1)}, \theta_2^{(t+1)}, \ldots, \theta_{j-1}^{(t+1)}, \theta_{j+1}^{(t)}, \ldots, \theta_k^{(t)}, y\right)$$

So as a result we get the new vector $\theta^{(t)}$ after updating t times equal to $\begin{pmatrix} \theta_1^{(t)} \\ \theta_2^{(t)} \\ \vdots \\ \theta_k^{(t)} \end{pmatrix}$

- The acceptance probability here is:

$$a(\theta_{-i}^{(t)}, \theta^{(t)}, \theta_i^*) = 1 .$$

- Since the proposal distribution $q\left(\theta_i^* \mid \theta_{-i}^{(t)}, \theta_i^{(t)}, y\right)$ for updating the i-th component of θ becomes the full conditional distribution $f_i(\theta_i^* \mid \theta_{-i}^{(t)}, y)$. Hence every new point is always accepted.

Convergence

An important issue in MCMC algorithms is convergence. There are several factors that must be taken into account for this topic (see for example in Congdon 2001, p.467). Problems with small data sets or few parameters achieve convergence faster. Furthermore, the sampling scheme as well as the parametrization used play a substantial role in convergence speed. In addition the closeness of the starting value to that of the stationary distribution is also important.

In MCMC algorithms we need to specify the number of chains, the starting values, the burn-in iterations and the total number of iterations (i.e. when the algorithm is terminated).

Concerning the number of chains, three different views have been proposed in literature: to use one very long chain, many long ones or finally to generate many short chains. However, the prevalent idea is to use the first or the second approach. Another important aspect here is the choice of the starting values. Their specification varies from problem to problem and strongly depends on the mixing of the chain. The number of burn-in iterations also depends on the starting values. The number of the burn-in iterations can be specified by specific convergence diagnostics described below (Gelman and Rubin, 1992; Raftery and Lewis, 1992; Geweke, 1992).

From another point of view, Geyer (1992) proposed that is sufficient to consider as the burn-in period between the 1% and the 2% of the total number of iterations. One way to determine the length of the chain is to run a number of chains with different starting values and then to examine whether all chains give the same results or not. If the results do not coincide then we need to generate chains of larger length (Gilks, Richardson and Spiegehalter, 1996 p.13).

Gelman and Rubin's Diagnostic Test

The diagnostic proposed by Gelman and Rubin (1992) is a univariate diagnostic and can be applied to two or more parallel chains. Under the assumption of m parallel chains with different starting points, run these chains for 2n iterations and then the aim is to check whether the variation within chains equals to the variation between the chains for the last n iterations. This convergence can be monitored by estimating the *"scale reduction factor"*:

$$\sqrt{R} = \sqrt{\left(\frac{n-1}{n} + \frac{m+1}{mn}\frac{B}{W}\right)\frac{df}{df-2}}\,.$$

Where $\frac{B}{n}$ denotes the variance between the means of the m-parallel chains, W is the average of the m-within chain variances and df denote the degrees of freedom of t-density which is an approximation to the posterior density. This factor ($\sqrt{R}$) tends to 1 for $n \to \infty$ and is the quantity by which the scale parameter will be shortened if sampling repeats infinitely.

Geweke's Diagnostic Test

Geweke (1992) proposed to consider the values of the sequence $\{g(\theta^t)\}$, as a time series. Here we have two different portions of Gibbs of size n_A, n_B , respectively. Finally let's consider $S_g^A(.)$, $S_g^B(.)$, the estimates of their spectral densities. An estimation of the means of g function for these two portions of Gibbs sampling is:

$$\bar{g}_{n_A} = \frac{\sum_{t=1}^{n_A} g(\theta^t)}{n_A} \quad , \quad \bar{g}_{n_B} = \frac{\sum_{t=1}^{n_B} g(\theta^t)}{n_B}$$

For the fixed ratios $\frac{n_A}{n}, \frac{n_B}{n}$ and for $\frac{n_A + n_B}{n} < 1$, the convergence diagnostic is:

$$\frac{\bar{g}_{n_A} - \bar{g}_{n_B}}{\sqrt{\frac{1}{n_A} S_g^A(0) + \frac{1}{n_B} S_g^B(0)}} \to N(0,1), \text{ for } n \to \infty$$

The above diagnostic is nothing else than an application of central limit theorem having taken as $n_A = \frac{n}{10}$ the first 10% of the total Gibbs sample and as $n_B = \frac{n}{2}$ the last 50% of the Gibbs sample and checks the null hypothesis :

$$H_0 : \bar{g}_{nA} = \bar{g}_{n_B} .$$

Raftery and Lewis's Diagnostic Test

Raftery and Lewis (1992) proposed another diagnostic test for convergence. This test depends on the estimation of the quantiles of the posterior distribution of a function $f(.)$ of the parameters for a required probability of attaining a known degree of accuracy. If we wish to estimate the posterior quantile $P(f < u \mid y)$ within an interval of $\pm r$ units with probability α, we start this Gibbs sampler initially for some iterations suppose n and then we repeat for N iterations of which we accept every k-th sample after burn-in. Hence we simply have to run the sampler in order to determine n, N and k. In literature the values to use $n = 1000$, $N = 10000$ and $k = 10$ or 20 (Besag, York and Mollie, 1991). In the case of $k > 1$ then we have to use all the N generated values. On the other hand for k large enough the generated samples are independent.

Heidelberger and Welch's Diagnostic Test

Heidelberger and Welch's (1983) diagnostic test is an application of Brownian bridge statistics. According to this test we generate a sequence of $X_1, \ldots, X_n$ that converges to X and we consider them as a time series with a spectral density at zero $S(0)$. Then we create confidence interval for the expected value of X and use the width of this interval to estimate the total run length. This sequence follows a normal distribution with variance:

$$\frac{S(0)}{n} = \sum_{k=-\infty}^{\infty} \gamma(k)$$

$\gamma(k)$: This is the covariance function.

for ε : be a determined requirement and the estimated relative half-width:

$$ERHW = \frac{Confidence\ Interval\ width}{2\overline{X}}$$

If $ERHW \leq \varepsilon$ then the chain is successfully stopped in the opposite case it fails and we need to run a chain of larger length.

Moreover in this test we have to examine whether or not the samples come from a stationary process. There are several tests for testing this null hypothesis of stationarity (Cramer-von Mises's, Anderson-Darling's, Kolmogorov-Smirnov's and Schruben's). If the null hypothesis is rejected then the initial 10% of the sequence is removed and repeat the test for the rest of the sequence. The property of stationarity is succeeded if at least the half of the observations has passed the test. In this case we conclude that the chain has reached convergence.

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