Job Insecurity and Mental Health from a Spillover-Crossover Perspective
– Multilevel Modeling of Longitudinal Dyadic Data

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List of Abbreviations

-2LL	-2 log likelihood
AIC	Akaike Information Criterion
APIM	Actor-Partner Interdependence Model
AUC	Area Under Curve
BHPS	British Household Panel Survey
BIC	Bayesian Information Criterion
CFA	Confirmatory Factor Analysis
ECHP	European Community Household Panel Survey
EFA	Exploratory Factor Analysis
e.g.	exempli gratia/for example
EQ-5D	EuroQol EQ-5D Quality of Life Scale
ERI	Effort-Reward Imbalance
GHQ	General Health Questionnaire
GSOEP	German Socio-Economic Panel
HILDA	Household, Income and Labour Dynamics in Australia Survey
ICC	Intraclass Correlation Coefficient
i.e.	id est/that is
ILO	International Labour Organization
IQOLA	International Quality of Life Assessment
ISCO	International Standard Classification of Occupations
ISTAT	Italian National Institute of Statistics
MCS	Mental Component Summary Scale
MHI-5	Mental Health Inventory
ML	Maximum Likelihood Estimation

MLM	Multilevel Modeling
MOS	Medical Outcome Study
MRRS	Michigan Recession and Recovery Study
N	Number of Observations
NHP	Nottingham Health Profile
PCS	Physical Component Summary Scale
RLMS	Russian Longitudinal Panel Survey
ROC	Receiver Operating Characteristic
SD	Standard Deviation
SEM	Structural Equation Modeling
SF-12	12-Item Short-Form Health Survey
SF-36	36-Item Short-Form Health Survey
TWIN	Tokyo Work-Family INterface Study
USA	United States of America
VicHealth	Victorian Health Promotion Foundation
VIF	Variance Inflation Factor
vs.	versus
WFHN	Work, Family & Health Network Study
WHO	World Health Organization
WSI	Wirtschafts-und Sozialwissenschaftliches Institut

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Sonja G. Schatz

1 Introduction

1.1 Motivation

Typical employment, characterized by permanence and full-time employment, is no longer representative for labor markets worldwide (Benach and Muntaner 2007; Hinterseer 2013; International Labour Organization (ILO), 2015). A growing share of individuals work in atypical employment, which is defined as the opposite term of typical employment (Brehmer and Seifert, 2008; Hinterseer, 2013) and hence, represented by temporary employment, temporary agency work, part-time employment or minor employment (Wirtschafts-und Sozialwissenschaftliches Institut (WSI), 2016). Six out of ten employees are nowadays part-time or temporary employed (ILO, 2015). Furthermore, only less than 45% of the workers worldwide are employed in a full-time job and on a permanent contract. Thereby, the rising atypical employment is associated with a lack of security with important economic and social consequences. The ILO estimates a loss in global demand because of unemployment, lagging labor incomes and resulting effects of consumption of about $3.7 trillion (ILO, 2015).

In Germany, 39.6% of all working individuals are atypically employed in 2016. Thereof, 23% are temporary employed, 2.6% are employed in temporary agency work and 14.1% are working exclusively in a mini-job (WSI, 2017). Thereby, the development of atypical employment in Germany has shown a steady rise since 2008 (WSI, 2017). These numbers would however be even higher, when atypical employment is defined more detailed than just as the opposite term of typical employment. If atypical employment is rather understood in terms of precarious employment, the problem of an increasing share of this kind of employment could be examined even much more detailed (Brehmer and Seifert, 2008; Kalleberg, 2014).

In 2012, the ILO defines precariously employed individuals in the course of examining precious employment as individuals, who suffer from job insecurity, who have few design possibilities of their work situation, mini-jobber, medi-jobber, individuals in temporary agency work or temporary employment and individuals, who obtain welfare benefits besides their regular labor income to secure subsistence (ILO, 2012). A conceptual and theoretical discussion about the concept of precarious employment thereby is not only existing since the rising share of precariously employed individuals in the past years. Already in 1989, Rodgers and Rodgers address precarious employment and develop four central dimensions of precarious employment. Those dimensions are later

named as the temporal dimension, the organizational dimension, the social dimension and the economic dimension and are still applied in research today (Brehmer and Seifert, 2008; Hinterseer, 2013; Kalleberg, 2014). Thereby, the temporal dimension is related to the permanence of employment, whereas precarious employment is associated with a short time horizon or a high risk of job loss (Rodgers and Rodgers, 1989). The organizational dimension however refers to the control over working conditions. The organizational dimension is linked to the temporal dimension in so far, that the less the worker's control the more insecure the work is (Rodgers and Rodgers, 1989). The social dimension is related to the protection of work due to for example laws or collective organizations. Finally, the economic dimension is about income, where income, which does not ensure social insertion, can be classified as precariously (Rodgers and Rodgers, 1989).

These definitions of precarious employment show, that precarious employment goes beyond the form of work, as it encompasses different factors, making employment unstable, unprotected and social as well as economically vulnerable (Benach and Muntaner, 2007; Brehmer and Seifert, 2008; Kalleberg, 2014). Therefore, precarious employment is broader than atypical employment, because even typical employment can be precarious for example due to a lack of a social safety net in a given country. Furthermore, atypical employment can also not be precarious or be perceived as not precariously. Some part-time employments for example may be desired as well as secure and stable. Also temporary employment may not be perceived by employees as precariously but as flexible (Benach and Muntaner, 2007; Kalleberg, 2014).

Against this background, also the difficulty of measuring precarious employment becomes apparent, because only observing the form of work does not lead to the desired result (Kalleberg, 2014). Therefore, the aspect of insecurity in the precarious employment definition gains in importance for detecting precarious employment. Insecurity of a job is not just objective measurable by for example a temporary contract, but also and especially identifiable by subjective measurement, which enables to detect precarious employment beyond the form of work (Benach and Muntaner, 2007; Kalleberg, 2014). Job insecurity with the meaning of the subjective concern about the permanence of a job is a frequently examined subject of research (De Witte, 1999; Hellgren et al., 1999; Sverke et al., 2002; Benach and Muntaner, 2007; Otterbach and Sousa-Poza, 2016; Reichert and Tauchmann, 2017; De Witte et al., 2016; Shoss, 2017). The permanence of a job is thereby to be understood in terms of quantitative job insecurity, which especially means the termination of the employment contract

followed by unemployment.[1] Next to the detection of precarious employment in terms of subjective job insecurity, the related consequences of job insecurity are also of particular interest (Sverke et al., 2002; Benach and Muntaner, 2007).

Sverke et al. (2002) divide these consequences based on a meta-analytic review of empirical results of job insecurity into individual and organizational consequences. Individual and organizational consequences are additionally differentiated between immediate and long-term consequences (Sverke et al., 2002). Immediate organizational consequences represent organizational attitudes like commitment, long-term organizational consequences however are assigned to work related behavior like turnover or performance. Immediate individual consequences are related to job attitudes like job satisfaction, whereas long-term individual consequences represent health related consequences (Sverke et al., 2002).[2]

Regarding theoretical considerations based on the Job Demands-Resources Model by Demerouti et al. (2001), especially health related consequences of job insecurity are covered. The Job Demands-Resources Model deals with consequences of job conditions, whereas job conditions are divided into job resources and job demands (Demerouti et al., 2001). Job resources cause a motivational process, leading to higher engagement or better performance. The existence of job demands however causes a health impairment process with negative consequences like exhaustion or burnout. Following the Job Demands-Resources Model, job insecurity as a typical job demand leads to health impairment (Demerouti et al., 2001; Bakker and Demerouti, 2013; Schaufeli and Taris, 2014). Job insecurity in terms of a subjective experience is found to be especially associated with mental health consequences (Sverke et al., 2002). Several studies have empirically confirmed this relationship between job insecurity and the mental health status until today (see e.g. Kopp et al. (2007), Bethge et al. (2008), Lam et al. (2014), Tomas and Seršić (2015), Otterbach and Sousa-Poza (2016), Cottini and Ghinetti (2017) or Reichert and Tauchmann (2017)).[3] The empirical evidence thereby displays that job insecurity has negative consequences for mental health across different countries and cultures. This is es-

[1] Qualitative job insecurity however means a loss of specific job features and hence a change of the current job and not a termination of the employment contract in general. The differentiation between qualitative and quantitative job insecurity was introduced in 1990 by van Vuuren and Klandermans. See also Heaney et al. (1994) and Davy et al. (1997).

[2] A graphic representation of the different consequences can be found in Figure 18 in the Appendix.

[3] For an overview of studies examining job insecurity and mental health, see e.g. Kim and von dem Knesebeck (2015) or De Witte et al. (2016).

pecially interesting with regard of existing divergence of uncertainty avoidance across countries examined by Hofstede (1984, 2003); Hofstede et al. (2010); Hofstede and Hofstede (2012), which is obviously not reflected considering job insecurity.

In 2013, the Spillover-Crossover Model was developed by Bakker and Demerouti based on the Job Demands-Resources Model. The Spillover-Crossover Model combines two different ways of the transmission of work-related experiences, spillover and crossover. A spillover represents an intra-individual transmission from one life domain of an individual to another life domain of this individual. A crossover however represents a transmission of experiences across individuals and hence represents a dyadic, inter-individual process (Bakker and Demerouti, 2013). Therefore, the Spillover-Crossover Model no longer only refers to the consequences of work-related experiences of one's own outcomes, but additionally implies that work-related experiences indeed first spill over to the home domain, but then also cross over to the partner's outcomes (Bakker and Demerouti, 2013).

After implementation of the Spillover-Crossover Model, the spillover process and the crossover process of several factors are empirically examined. Here, positive as well as negative spillover and crossover are considered. For example, Sanz-Vergel and Rodríguez-Muñoz (2013) analyze positive spillover and crossover of work enjoyment to well-being and find significant evidence for the Spillover-Crossover Model. Negative spillover and crossover can for example be found between emotional exhaustion and marital satisfaction by Liang (2015). Bakker et al. (2013) however confirm the Spillover-Crossover Model by examining spillover and crossover for work engagement as well as for workaholism on family satisfaction.[4]

1.2 Research Gap, Aim and Contribution

Because of the theoretical improvement arisen by the development of the Spillover-Crossover Model, also new assumptions regarding the relationship between job insecurity and the mental health status are conceivable. However, until now there is hardly any research on this relationship additionally considering the partner's situation and examining individuals, who are in a relationship with each other. Although previous literature already shows that a negative relation between the employment status of an individual, one's

[4] For more evidence, see e.g. Shimazu et al. (2011), Bakker et al. (2012), Demerouti (2012), Sanz-Vergel and Rodríguez-Muñoz (2013), Rodríguez-Muñoz et al. (2014), Steiner and Krings (2016) or Totenhagen et al. (2017).

own well-being and health status as well as partner's well-being and partner's health status, exists. For example, Luhmann et al. (2014) show for Germany, that unemployment lowers life satisfaction of both members of a couple. In addition, a negative relationship between an individual's unemployment and the mental health status of both couple members could be found for Germany by Marcus (2013).[5]

A holistic empirical examination of the Spillover-Crossover Model regarding job insecurity and the mental health status has hence not been considered until now. Spillover and crossover of job insecurity to the mental health status within two individuals, who established a relationship with each other, has hence not been a subject of research. Furthermore, even though empirical evidence for the general negative relationship between job insecurity and the mental health status has already been found, a current consideration based on the Spillover-Crossover Model for Germany is missing so far (for Germany between 1997 and 2010 see e.g. Bethge et al. (2008), Otterbach and Sousa-Poza (2016) or Reichert and Tauchmann (2017)). Next to this content related research gap, also a methodological one should be addressed. For an empirical examination of the Spillover-Crossover Model regarding job insecurity and the mental health status, a dyadic dataset and hence a dataset consisting of two individuals must be used to consider not only intra-individual spillover but also the inter-individual crossover (Kenny et al., 2006).

To analyze dyadic data and examine spillover as well as especially crossover within two individuals, an Actor-Partner Interdependence Model (APIM) can be estimated (Kenny et al., 2006). The APIM is a statistical model, that considers the influence of dyad members among each other and produces outcomes and predictors for both members of a dyad by estimating actor as well as partner effects. An actor effect is defined as the effect of an individual's own independent variable on the individual's own dependent variable and a partner effect as the effect of an individual's own independent variable on the partner's dependent variable (Kenny et al., 2006; Kenny and Ledermann, 2010).

The APIM has been estimated in recent years mainly using cross-sectional data (see e.g. Neff et al. (2013), Liu and Cheung (2015), Quaglia et al. (2015) or Bakker et al. (2016)) or short-term longitudinal data with two different

[5] A study by Bünnings et al. (2017) examines the fear of unemployment but only on spouse's mental health status in dual-income and single-income couples in Germany. Therefore, Bünnings et al. (2017) do not examine spillover and crossover in the meaning of the Spillover-Crossover Model and hence, do not give a holistic picture of spillover and crossover within a couple.

occasions (see e.g. Mushquash et al. (2013)).[6] Just few empirical research, considering the use of an APIM for longitudinal data (see e.g. Lersch (2013) or Hahn et al. (2014)), the so-called Over-time Standard APIM (Kenny et al., 2006) exists. Since it has only been used rarely until today, the estimation strategies of this model are not fully explored yet. In general, Multilevel Modeling (MLM) can be used to estimate an Over-time Standard APIM (Kenny et al., 2006), however there is no consent of how many levels should be modeled, while using longitudinal dyadic data.

First, longitudinal data conceptually represents three-levels, where occasions are assumed to be nested within individuals and individuals are assumed to be nested within dyads (Hoffman, 2015). However, when time is considered as fully crossed within dyads, as the members of a dyad are observed at the same occasions, a correlation between the outcomes of the dyad members for a given occasion may be expectable (Kashy and Donnellan, 2012; Bolger and Laurenceau, 2013). Regarding such crossed occasions and not assuming them as nested, longitudinal dyadic data is represented by two levels, where occasions are assumed to be crossed within individuals and individuals are assumed to be nested within dyads (Kashy and Donnellan, 2012; Bolger and Laurenceau, 2013; Hoffman, 2015). Until now there is hardly any research focusing on the contrast between three-level modeling and two-level modeling of an Over-time Standard APIM, using longitudinal dyadic data.

In summary, the content related and the methodological research gap lead to the following research questions. First, the question arises, whether a spillover of job insecurity to the mental health status of an individual exists. Second, whether a crossover of job insecurity to the mental health status of the individual's partner, enrolled in a relationship with the individual, exists. This means in particular, whether the Spillover-Crossover Model of job insecurity and the mental health status in general can be empirically confirmed.

Since, Bakker and Demerouti (2013) display the Spillover-Crossover Model differentiated by women and men, it is suggested to have a closer look at this gender differentiation regarding the asked research questions, as well. The theoretical basis, represented by the Social Role Theory by Alice H. Eagly with one of its central issues, that the family and the work role are differently adopted by women and men, leads to two additional research questions which are not answered in research until today. Therefore, a third research question arises, whether spillover of job insecurity is differently pronounced for women and

[6] Kenny and Ledermann (2012) give an overview of all articles, using an APIM for analysis up to 2012. Only less than 5% of these studies are using longitudinal data.

men. Furthermore, it leads to a fourth research question, whether crossover of job insecurity is differently depending on gender. Finally, a fifth research question, arising by the methodological research gap, explores whether the empirical evidence for the Spillover-Crossover Model differentiated by women and men, should be conducted using three-level modeling or using two-level modeling, while using longitudinal dyadic data.

Three aims will thereby be pursued in the present thesis. The first aim of the thesis is the theoretical processing of the relationship between job insecurity and the mental health status in consideration of spillover and crossover as well as under the aspect of gender differences. The second aim comprises to make a contribution to the theory development of spillover and crossover, by verifying the theoretical considerations using longitudinal dyadic data representative for Germany. Finally, the third aim of the thesis comprises the presentation, comparison and evaluation of two different estimation strategies to additionally make a contribution to the methodical approach for longitudinal dyadic data.

1.3 Research Methodology and Thesis Structure

The achievement of these aims is encouraged by the structure of the thesis. Chapter 2 displays the basic terminology. The development of the job insecurity definition is represented chronologically and different dimensions of the job insecurity definition are elaborated. The different dimensions are discussed and the establishment of a definition on a global level is argued. The possibilities of measuring job insecurity, to be found in empirical research until today, are presented and the determination of an unidimensional single-item measurement is explained. The term *mental health* is defined and delimited against well-being. Additionally, methods for measuring mental health are displayed and the used measuring method is represented in detail. Chapter 3 displays the theoretical foundation. The Spillover-Crossover Model is represented as the theoretical basis for the relationship between job insecurity and the mental health status. In the course of the presentation also the empirical evidence supporting the Spillover-Crossover Model is displayed, and the Theory of Emotional Contagion (Hatfield et al., 1993) and the Social Identity Theory (Tajfel and Turner, 1979) are introduced as an additional theoretical basis for crossover. Afterwards, the Social Role Theory is described to consider gender differences regarding spillover and crossover of job insecurity on the mental health status. Furthermore, the Social Role Theory is discussed against the background of changing times since its development.

Based on the theoretical foundation, hypotheses regarding spillover and cross-

over of job insecurity to the mental health status for women and men as well as differences, arising by gender are developed in Chapter 4. The used data for the empirical examination of the established hypotheses is presented in Chapter 5. Thereby, the used dataset, the German Socio-Economic Panel (GSOEP) is represented as well as the specific sample restriction for the following analysis. Additionally, the used variables and the corresponding measuring methods are displayed. In chapter 6, the methodological bases and the development of an estimation strategy of the analysis of longitudinal dyadic data of job insecurity and mental health are presented. Therefore, the general concept of MLM is introduced firstly. This is followed by an overview of MLM for longitudinal data, including the peculiarity of longitudinal data and the standard multilevel models for longitudinal data. After this, MLM of dyadic data is presented by displaying the peculiarity of dyadic data and introducing MLM of an APIM. The methodological bases of longitudinal data and dyadic data then are combined to develop an estimation strategy for a combination of longitudinal and dyadic data and hence, longitudinal dyadic data and especially with regards to longitudinal dyadic data of job insecurity and mental health.

The empirical evidence, presented in Chapter 7, is divided into the descriptive analysis and the analysis considering the Over-time Standard APIM. The descriptive analysis displays statistics about the underlying data as well as the correlation matrix of the used variables. The analysis considering the Over-time Standard APIM, is divided into the MLM using three-levels and the MLM using two-levels. These subchapters represent the estimation results of the three-level MLM and the two-level MLM as well as some robustness checks. A subchapter, comparing the results of the two-level MLM with those of the three-level MLM follows. The assumed hypotheses are verified in course of the results' presentation within the respective subchapters. The empirical results are generally discussed with regards to the background of the theoretical foundation and previous research in Chapter 8. The discussion of the limitations of the thesis are presented in Chapter 9. Finally, Chapter 10 will give a summary of the main findings and make recommendations for future research.

2 Basic Terminology

2.1 Job Insecurity

2.1.1 Definition

Job insecurity and respectively job security is a topic, which is often examined in different research fields like psychology, social science, personnel or behavior science. Accordingly, there is a variety of definitions existing in literature (Sverke et al., 2002; Shoss, 2017). Contrary to satisfaction and dissatisfaction, which are not assumed to represent the extreme forms of one continuum, but two different continua (Herzberg, 1986), job insecurity and job security are assumed to represent the extreme forms of one continuum (Johnson et al., 1984; Sverke et al., 2002; Virtanen et al., 2002). This approach of job insecurity is in line with ethics about risk. In this field, insecurity is generally presented at a continuous range between the extreme forms, completely insecure and completely secure (Nida-Rümelin et al., 2012). Transferred to the work context, job insecurity can also be assumed to represent the opposite term of job security and leads to the relationship that no job security equals job insecurity and that no job insecurity equals job security (Virtanen et al., 2002). This also results due to factually logical considerations, because a simultaneous existence of being job insecure and of being job secure is not possible. In the existing literature, the term *job insecurity* is used more often than the term *job security* to describe the continuum, especially when negative consequences are considered (Sverke et al., 2002; Virtanen et al., 2002). Therefore, in the following, the common term *job insecurity* will also be primarily used.

Shoss (2017) presents a sample collection of definitions of job insecurity between 1984 and 2016. This list of definitions makes no claim to be exhaustive, but is a good starting point for an overview of the various definitions existing in literature. Based on the list of definitions presented by Shoss (2017), the primary sources will be analyzed and further definitions will be selected to get a holistic picture of the definitions of job insecurity. In order to display also the development of the various definitions of job insecurity, the presentation is executed chronologically. The chronological overview is divided into two parts, definitions until 1999 and definitions after 1999. This proceeding is chosen to meet another review of job insecurity definitions drawn up by Sverke et al. (2002), who gather definitions of job insecurity between 1980 and 1999, which are not totally included in the review by Shoss (2017). Due to the overview of definitions until 1999, different dimensions of job insecurity can be derived

and are listed. After this, the chronological overview of definitions after 1999 follows. The list of dimensions until 1999 is then expanded with dimensions detected after 1999 in order to get a holistic picture of job insecurity dimensions and corresponding definitions until today.

Shoss (2017) starts with the definition of job insecurity from Greenhalgh and Rosenblatt (1984), which is considered as one of the first definitions of job insecurity in literature. Greenhalgh and Rosenblatt (1984) define job insecurity as a feeling of an individual's powerlessness towards the continuance of an employment situation at risk. In 1990, van Vuuren and Klandermans focus on concerns of individuals rather than feelings of powerlessness (van Vuuren and Klandermans, 1990). Additionally, two other aspects are illuminated by the definition of van Vuuren and Klandermans (1990). They emphasize a future perspective of job insecurity and differentiate between job insecurity of the job itself and job insecurity of the job conditions. Summarizing, van Vuuren and Klandermans (1990) define job insecurity as concerns about the stability of a job itself or of its conditions in the future.

Another definition presented by Shoss (2017) comes from Jacobson and Hartley (1991) and includes a comparison of the preferred and the actual situation. They define job insecurity as the difference between the preferred level of security by an individual and the actual level, the individual experiences. Heaney et al. (1994) however, define job insecurity as a potential threat, perceived by an individual, towards the job of this individual. De Witte (1999) chooses a similar definition as van Vuuren and Klandermans in 1990 and defines job insecurity as an overall concern about the existence of a job in the future. Also in 1999, the differentiation between the job itself and the different job features or conditions already made by van Vuuren and Klandermans in 1990 are taken up again and specifically named by Hellgren et al. (1999). They state the definition of job insecurity, as a concern about future existence of a job itself, as quantitative job insecurity. The definition of job insecurity, as a concern about future existence of job features is stated as qualitative job insecurity (Hellgren et al., 1999).

In order to complete the picture of job insecurity definitions given until 1999, it is continued with the representation of the definitions included in the review by Sverke et al. (2002), who elaborate a review of job insecurity definitions between 1980 and 1999. All definitions are represented, which are not included in the study by Shoss (2017) and which do not directly refer to one of the definitions already displayed.

One of the definitions mentioned by Sverke et al. (2002) comes from Lim

(1996), who defines job insecurity as a highly stressful phenomenon, because of the ambiguity of the existence of a job. A definition by Barling and Kelloway (1996) refers to the feeling of powerlessness already introduced by Greenhalgh and Rosenblatt (1984). Barling and Kelloway (1996) define job insecurity as a function of a perceived lack of control. Davy et al. (1997) define job insecurity as expectations about the continuity of a job or its features. In 1998, Pearce defines job insecurity as a psychological state and executes that employees in such a psychological state vary in their expectations about the continuity of their job in a given organization in the future (Pearce, 1998). Bussing (1999) however focuses on uncertainty as a central quality of job insecurity next to an existing threat and the powerlessness to deal with the threat, which is already mentioned by Greenhalgh and Rosenblatt in 1984. Thereby, he differentiates between four facets of uncertainty associated with job insecurity. The first facet is the general uncertainty, if unemployment will occur. The second facet is the uncertainty in time, when unemployment will occur and the third facet is the uncertainty in content, in which way unemployment will occur. The last facet is the uncertainty of the outcomes, which results in unemployment (Bussing, 1999).

The summary of the job insecurity definitions until 1999, presented above, shows different and repetitive dimensions concerning the definition of job insecurity. Thereby, some definitions contain several of these dimensions. Nevertheless, it is considered that it is useful to differentiate between the following dimensions since a rough division would fail to meet the spectrum of definitions of job insecurity existing in literature. Hence, the following dimensions used in literature for defining job insecurity can be presented:[7]

- Powerlessness/loss of control toward a job loss (Greenhalgh and Rosenblatt, 1984; Barling and Kelloway, 1996; Bussing, 1999)

- Subjective expectation/feeling/concern about the continuance/existence of a job (van Vuuren and Klandermans, 1990; Jacobson and Hartley, 1991; Heaney et al., 1994; Davy et al., 1997; Pearce, 1998; De Witte, 1999; Hellgren et al., 1999)

- Uncertain/risky job future (Greenhalgh and Rosenblatt, 1984; Heaney et al., 1994; Lim, 1996; Bussing, 1999)

Following the differentiation, which was developed in 1994 by Heaney et al., these dimensions can refer to job insecurity concerning the job itself (quantita-

[7] The dimensions-list only includes dimensions which are mentioned in at least two of the presented studies.

tive job insecurity) or concerning specific job features (qualitative job insecurity).[8] In the following, it is concentrated on quantitative job insecurity. This is done, because quantitative job insecurity especially means the termination of the employment contract followed by unemployment, which represents a more serious consequence than qualitative job insecurity in which the employment contract is not being terminated. Qualitative job insecurity and hence a loss of specific job features means a change of the current job and not a termination of the employment contract in general, leading to unemployment. The decision to concentrate on quantitative job insecurity is in line with recent research about job insecurity, as Vander Elst et al. (2014) recommend to concentrate on the core of job insecurity and thus on quantitative job insecurity.

For definitions up to 1999, accordingly after the review of the job insecurity definition between 1980 and 1999 by Sverke et al. (2002), the sample collection by Shoss (2017) is again used as a starting point and expanded by an additional literature research to draw a holistic picture of the job insecurity definitions and dimensions, existing in literature until today. Thereby, it has to be considered that some definitions after 1999 displayed by Shoss (2017) are not the primary sources of these definitions. In such a case, only the primary sources will be presented. One example is the definition by Grunberg et al. (2006). They define job insecurity as an employee's feeling that her respectively his current job is at risk or that they are likely to perceive job loss. This definition is later adopted by Schreurs et al. (2012).

In 2000, a definition of job insecurity is presented by Manski and Straub, who directly focus on the subjective characteristic of job insecurity by defining job insecurity as the subjective probability, that a current job will be destructed exogenously. De Cuyper et al. (2008) define job insecurity as the perceptions of an employee about a potential involuntary job loss. This definition shows that in the middle of the 2000s another dimension associated with job insecurity was emphasized, the dimension of *involuntary job loss*. This dimension can also be found in the definitions by Burchell (2011), De Cuyper et al. (2012) and Vander Elst et al. (2014). Burchell (2011) defines job insecurity very similar to De Cuyper et al. (2008) as an employee's perception about the involuntary job loss probability and underlining the subjectivity of this perception. De Cuyper et al. (2012) expand the definition from De Cuyper et al. (2008) by including concerns about a potential involuntary job loss next to perceptions. Vander Elst et al. (2014) define job insecurity as a subjectively perceived and undesired possibility of losing the current job involuntarily in the future and

[8] A differentiation between job insecurity of the job itself and different job features is also made by van Vuuren and Klandermans (1990) and Davy et al. (1997).

the fear or worries associated with this job loss probability. Ellonen and Nätti (2015) however focus again on the subjectivity of job insecurity and define it as the evaluation of an employee about how likely it is that he respectively she will lose his respectively her job in the near future.

Finally, after presenting different definitions, Shoss (2017) focuses on the perceived threat for the continuity and stability of a job, the subjectivity and the future-orientation and defines job insecurity as a threat, perceived by an employee, regarding the continuity and stability of the job this employee experiences.

A further literature research on definitions of job insecurity identified one additional definition, which is not presented in the review by Shoss (2017). The definition is pointed out by Dachapalli and Parumasur (2012). They define job insecurity as a stressful event, anticipated by an employee because of a perceived risk concerning the nature and continuity of one's job, which only occurs in the case of involuntary job loss.

Comprehensively, one additional dimension is found in definitions after 1999 and can further be added to the dimensions-list. Furthermore, divers definitions can be added to the previous dimensions and the dimension of subjectivity can be expanded by further expressions to complete the picture of job insecurity dimensions developed until today:[9]

- Powerlessness/loss of control toward a job loss (Greenhalgh and Rosenblatt, 1984; Barling and Kelloway, 1996; Bussing, 1999)

- Subjective expectation/feeling/concern/perception/evaluation about the continuance/existence of a job (van Vuuren and Klandermans, 1990; Jacobson and Hartley, 1991; Heaney et al., 1994; Davy et al., 1997; Pearce, 1998; De Witte, 1999; Hellgren et al., 1999; Manski and Straub, 2000; Grunberg et al., 2006; De Cuyper et al., 2008; Burchell, 2011; Dachapalli and Parumasur, 2012; De Cuyper et al., 2012; Vander Elst et al., 2014; Ellonen and Nätti, 2015; Shoss, 2017)

- Uncertain/risky job future (Greenhalgh and Rosenblatt, 1984; Heaney et al., 1994; Lim, 1996; Bussing, 1999; Grunberg et al., 2006; Dachapalli and Parumasur, 2012)

- Threat of involuntary job loss (De Cuyper et al., 2008; Burchell, 2011; Dachapalli and Parumasur, 2012; De Cuyper et al., 2012; Vander Elst et al., 2014)

[9] A similar classification can be found in De Witte et al. (2012),Vander Elst et al. (2014) and De Witte et al. (2015).

Considering these dimensions, an encompassing definition of job insecurity can be drawn up, which considers the different dimensions existing in literature about job insecurity between 1984 and today. Job insecurity is a subjective expectation, feeling, concern, perception or evaluation in an uncertain or risky job situation about the continuity or existence of a job in the future without having the control or power to prevent an involuntary job loss.

However, such a definition consisting of different dimensions, is not purposeful, if one is interested in examining the relationship between job insecurity and other variables, because some of the dimensions may rather be moderators in such a relationship than really a dimension of job insecurity (Probst, 2003). The dimension of powerlessness or the loss of control is a property or characteristic of an employee and may include information about the relationship between job insecurity and another variable. For example, examining the effect of job insecurity (defined and measured with the aspect of powerlessness/loss of control) on health, any information regarding the moderator effect of such employees' characteristics on this relationship is lost. This of course could also apply to other dimensions.

Vander Elst et al. (2014) therefore recommend to focus on the core of job insecurity and left out factors like future-orientation, powerlessness (involuntary) or the importance of the job. Therefore, following Vander Elst et al. (2014) and leaving out other factors, in order not to loose information, the core of job insecurity is represented by the dimension of subjectivity. As presented above, this dimension is formulated somewhat differently in literature. The terms *expectation* (Pearce, 1998; Manski and Straub, 2000), *feeling* (Greenhalgh and Rosenblatt, 1984; Grunberg et al., 2006), *concern* (van Vuuren and Klandermans, 1990; De Witte, 1999; Hellgren et al., 1999; De Cuyper et al., 2008), *perception* (De Cuyper et al., 2008; Burchell, 2011; De Cuyper et al., 2012) and *evaluation* (Ellonen and Nätti, 2015) about the *continuity* (Greenhalgh and Rosenblatt, 1984; Davy et al., 1997; Pearce, 1998) or *existence* (De Witte, 1999; Hellgren et al., 1999; Sverke et al., 2002) are used to express the subjectivity of job insecurity.

To differentiate between these terms, it is referred to a division, which is developed in 1992 by Borg. He distinguishes between cognitive job insecurity and affective job insecurity. Thereby, he describes cognitive job insecurity as the perception about the likelihood of losing a job and affective job insecurity as the fear of losing a job, hence the feelings accompanied by job loss (Borg, 1992). Following the division by Borg (1992), a *feeling* about losing a job can be classified as affective job insecurity and an *expectation*, a *perception*, a *con-*

cern and an *evaluation* as cognitive job insecurity.[10] When considering these terms, it is appropriate to consider a *feeling* as a result of an *expectation*, an *evaluation*, a *perception* or a *concern*. This is in line with Huang et al. (2010), who propose that affective job insecurity is a result of cognitive job insecurity based on conceptualization of stress and Affective Events Theory (Huang et al., 2010). Considering again the recommendation by Vander Elst et al. (2014) to concentrate on the core of job insecurity already explained above, it is useful to focus on cognitive job insecurity and hence on the *expectation*, *evaluation*, *perception* or *concern* and not on the *feeling*, resulting by it, in order not to loose any information in research on job insecurity in relation to other variables or in research on the consequences of job insecurity.

Additionally, it is noticeable that with respect to the fundamental meaning of the words, *expectation* as well as *evaluation* or *perception* can be both, positive and negative. *Concern* however is in the general use of language negatively afflicted. Next to the fact, that the term *concern* is used most often, the executions show that *concern* fits best, considering the possible negative event of job loss and will hence be chosen for the job insecurity definition.

Concerning the terms *continuance* and *existence* in terms of a job, it is assumed that the terms are used as synonyms for the permanence of a job. Also the term *stability* (van Vuuren and Klandermans, 1990) which is used somewhat less in literature and therefore not added to the dimension-list, is assumed to be a synonym for permanence in a job. Finally, based on a job, also the term *security* used by Jacobson and Hartley (1991) is assumed as being a synonym for permanence. Therefore, the term *permanence* is chosen for the job insecurity definition to unite the different terms used in literature and the following definition of job insecurity is determined, *job insecurity is the subjective concern about the permanence of a job.* This definition is in line with the definitions by De Witte (1999) and the one by Hellgren et al. (1999) for quantitative job insecurity and includes the understanding of job insecurity as one continuum with the extreme forms, completely job insecure and completely job secure. In addition, this definition is described by Sverke et al. (2002) as the most used definition and an often reflected one in the measurement of job insecurity (Sverke et al., 2002).

[10] This classification of the terms is against the background of cognitive and affective job insecurity by Borg (1992) and does not make any claims to a differentiation between cognitive and affective in general.

2.1.2 Measurement

The variety of different definitions can also be found in the various ways of measuring job insecurity (Shoss, 2017). Since there are definitions of job insecurity containing different dimensions and definitions at a global level, the measures of job insecurity display this difference as well. The measures of job insecurity can therefore be roughly divided into multidimensional measures and unidimensional measures[11] as shown in Figure 1 (Mauno et al., 2001; Reisel and Banai, 2002; Sverke et al., 2004; O'Neill and Sevastos, 2013; Vander Elst et al., 2014). Multidimensional measures present, differently than unidimensional measures, various dimensions of job insecurity like the threat of loosing a job or the lack of control toward a job loss (Vander Elst et al., 2014). Consequently, multidimensional measures are always multi-item measures which means that job insecurity is elaborated with more than one item, where each item is a single question or statement (Sverke et al., 2004). Using unidimensional measures, job insecurity is measured on an overall level (Sverke et al., 2004). Thereby, unidimensional measures can be multi-item measures or single-item measures which try to capture job insecurity with one question or statement (one item) (Sverke et al., 2004). Whether unidimensional or multidimensional, job insecurity is almost exclusively self-reported.[12]

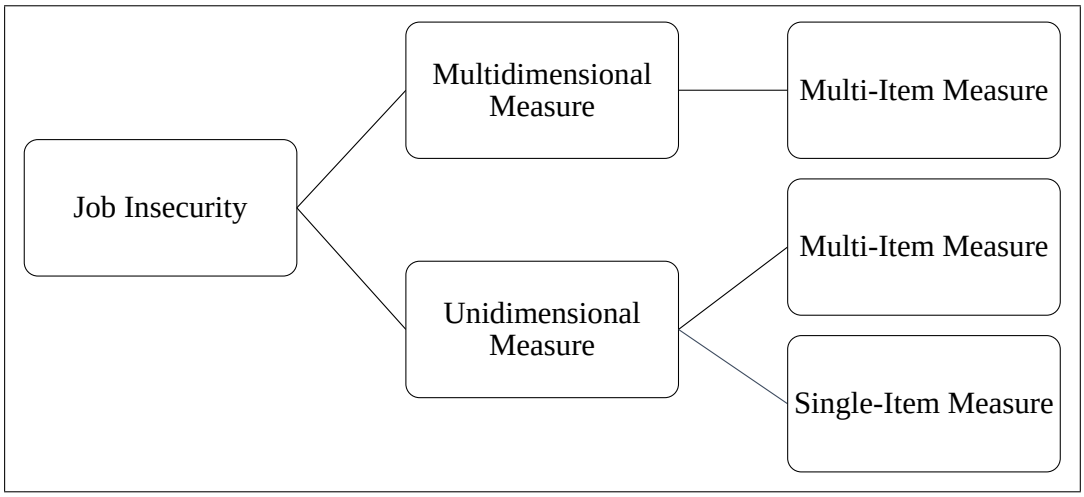

Figure 1: Job Insecurity Measures
(Source: Own presentation.)

[11] Also called global measures (e.g. Mauno et al. (2001); Reisel and Banai (2002); Sverke et al. (2004); Vander Elst et al. (2014)) or one-dimensional measures (e.g. Sverke et al. (2004); Vander Elst et al. (2014)).

[12] Nevertheless, there is also a possible objective operationalization of job insecurity. Thereby, temporary employment is considered as an indicator of this objective operationalization (Pearce, 1998). However, objective operationalization of job insecurity will not be pursued further, as it is not often used in literature and not in line with the existing definitions of job insecurity presented in Chapter 2.1.1.

An example for a multidimensional measure of job insecurity is the 57-item Job Insecurity Scale developed by Ashford et al. (1989). The Job Insecurity Scale as a whole or a selection of items corresponding to different dimensions, is often used in literature (e.g. Kinnunen et al. (2000); Mauno et al. (2001); Sverke and Hellgren (2001); Näswall et al. (2005b)) and is based on the definition of job insecurity by Greenhalgh and Rosenblatt (1984) who define job insecurity as a feeling of powerlessness of an individual toward the continuance of an employment situation at risk. Ashford et al. (1989) include the importance of the job itself and the importance of the job features, the threat of the job itself and the threat of the job features as well as the powerlessness to prevent a job loss, as dimensions of job insecurity in their multidimensional Job Insecurity Scale.[13] All dimensions are divided into different components, which are questioned using 5-point scales to rate importance of the job, the probability of loosing a job or to agree or disagree in the dimension of powerlessness (Ashford et al., 1989). After the collection of data through the Job Insecurity Scale, the overall perception of job insecurity is determined by Ashford et al. (1989) using a specific equation which includes the different dimensions of job insecurity.[14]

Ashford et al. (1989) test the reliability of the Job Insecurity Scale by calculating internal consistency using Cronbach's α. Cronbach's α, developed in 1951 by Cronbach, measures internal consistency and hence the extent to which certain items of a questionnaire measure the same construct (Cronbach, 1951; Tavakol and Dennick, 2011). Cronbach's α ranges between 0 and 1 and a value of at least 0.7 is mostly assumed in literature to be satisfactory (Ferketich, 1990; Schmitt, 1996; Gerpott and Paukert, 2011). When using Cronbach's α as a measure of internal consistency, it has to be considered that the value of Cronbach's α is affected by the number of items, item interrelatedness and dimensionality (Cortina, 1993). Acceptable values of Cronbach's α of at least 0.7 can even be achieved by low average item intercorrelation and multidimensionality, when the number of items is high (Cortina, 1993). In contrast, a value of Cronbach's α below 0.7 can also be acceptable, when a measure for example represents meaningful content coverage or reasonable unidimensionality (Schmitt, 1996). The interpretation of Cronbach's α should therefore always be made in an overall context and done critically. Ashford et al. (1989) find

[13] A short version of the Job Insecurity Scale by Ashford et al. (1989) can be found in Lee et al. (2008). Lee et al. (2008) develop a version with 37 items, including items for total job, job features and for powerlessness.

[14] The equation is specified as follows:
$\text{Job Insecurity} = [(\sum \text{Importance of Job Feature} \times \text{Likelihood of Losing Job Feature}) + (\sum \text{Importance of Job Loss} \times \text{Likelihood of Job Loss})] \times \text{Perceived Powerlessness to Resist Threat.}$

values for Cronbach's α which rank between 0.74 and 0.92 for all the different components of job insecurity (Ashford et al., 1989). Therefore, Ashford et al. (1989) assume that reliability is given for all the different components of job insecurity which are examined, because the critical value of 0.7 is reached by all of them. Furthermore, while developing the Job Insecurity Scale, Ashford et al. (1989) assume that the Job Insecurity Scale complies the criterion of convergent validity, because of correlations of 0.48 respectively 0.35 with two unidimensional job insecurity measures. Correlation coefficients thereby range between -1 and 1 whereas values smaller than ± 0.10 are classified as minor. Values greater or equal than ± 0.10 and smaller than ± 0.30 are considered as small. Values greater or equal than ± 0.30 and smaller than ± 0.50 are classified as moderate and values greater or equal than ± 0.5 considered as large (Cohen, 1988; Cohen et al., 2003). The other unidimensional job insecurity measures which are used by Ashford et al. (1989) are a scale developed by Caplan and Jones (1975) consisting of four items which are questioned using a 5-point response format and a scale developed by Johnson et al. (1984), consisting of seven items and also five response options. The internal consistency of the scales are indicated with a Cronbach's α value of 0.73 respectively 0.44 in the study by Ashford et al. (1989).

Isaksson et al. develope another multidimensional measure, first presented in 1998 in Swedish and later used in English amongst others, in a study by Hellgren et al. (1999). Their multidimensional measure captures two dimensions of job insecurity. On the one hand, the perceived threat to the job itself, and hence the quantitative job insecurity and on the other hand the perceived threat to the job features, hence the qualitative job insecurity (Hellgren et al., 1999). Both dimensions are together questioned with seven items and a 5-point Likert scale ranging from 1, representing a strong disagreement, to 5, representing a strong agreement. The dimensions are found by Hellgren et al. (1999) using Exploratory Factor Analysis (EFA)[15]. The internal consistency for quantitative job insecurity and qualitative job insecurity is represented using Cronbach's α, which display values of 0.79 respectively 0.74 (Hellgren et al., 1999). The quantitative job insecurity and qualitative job insecurity indices are calculated by the mean values of the corresponding items of each dimension. An overall job insecurity encompassing quantitative and qualitative job insecurity is not calculated (Hellgren et al., 1999).

Another example for multidimensional measures comes from O'Neill and Sev-

[15] EFA is a statistical method to identify an unknown underlying structure in a dataset. For more information see e.g. Fabrigar and Wegener (2011) or Weiber and Mühlhaus (2014). For advanced information see Patil et al. (2008).

astos (2013) using 18-items to measure job insecurity with a 7-point Likert scale ranging from 1 (very inaccurate) to 7 (very accurate). They depict four dimensions of job insecurity, job loss insecurity, job change insecurity, organizational survival insecurity and marginalization insecurity. These four factors are identified by O'Neill and Sevastos (2013) using EFA followed by Confirmatory Factor Analysis (CFA)[16]. The four factor model represents, in comparison to a null model, the best model fit for the used data. Tests of invariance across loadings as well as factor covariances and error covariances maintain using two samples. The sample used by O'Neill and Sevastos (2013) for generating items consists of observations of employees in a downsizing Australian private sector company. For validation they use a large North American media company raised by self-disclosure. The sample is divided into two random samples of $N = 502$ observations. One sample for the EFA and one for the CFA, which was then additionally divided randomly into two samples for calibration sample and cross-validation sample (O'Neill and Sevastos, 2013). Additionally, O'Neill and Sevastos (2013) test the internal consistency of the four dimensions and find values for Cronbach's α above 0.7 for each of the dimensions. The four dimensions are calculated using the unweighted average of the corresponding items in each dimension. An overall job insecurity is however not calculated (O'Neill and Sevastos, 2013).

Generally, authors use multidimensional measures to capture different dimensions of job insecurity, often derived from a definition with several dimensions. However, measuring several dimensions of job insecurity in contrast to an overall level (unidimensional measure) has some disadvantages. Like already mentioned above, concerning a multi-dimensional definition, a dimension can even be a moderator in the relationship between job insecurity and an outcome variable or can be in a direct relationship with job insecurity. When measuring this dimension as a part of job insecurity, all information about such relationships are lost (Probst, 2003; Vander Elst et al., 2014). Some authors therefore use only subscales of multidimensional measures and do not combine the measures of the different dimensions to one total measure of job insecurity (Kinnunen et al., 2000; Mauno et al., 2001; Sverke and Hellgren, 2001). Additionally, multidimensional measures are essentially longer than unidimensional measures, which makes it difficult to survey large samples and hence, also from a practical point of view, unidimensional measures are rather recommended (Vander Elst et al., 2014).

[16] CFA is an inference-statistical procedure to test if the measurement of a specific construct is in line with the adopted nature of this construct. For more information see e.g. Brown (2014) or Backhaus et al. (2015).

While measuring job insecurity, it could be found, that unidimensional measures using multi-item measuring correspond to multidimensional measures concerning construct validity and reliability (Mauno et al., 2001). Mauno et al. (2001) compare the use of an unidimensional job insecurity scale and a multidimensional measure, including the dimensions job importance, job loss probability and powerlessness using panel data of Finland. Reliability is examined in terms of internal consistency using Cronbach's α, which is calculated for each of the used three waves of the panel data. Additionally, they use multiwave, multi-variable models and longitudinal CFA to test construct validity (Mauno et al., 2001). The Cronbach's α value for the unidimensional measure amounts to 0.83 at time 1, 0.79 at time 2 and 0.79 at time 3 (Mauno et al., 2001). For the dimension job importance of the multidimensional measure, the Cronbach's α values amount to 0.62 at time 1, to 0.76 at time 2 and to 0.64 at time 3. For the dimensions job loss probability and powerlessness, Cronbach's α values of 0.70 respectively 0.67 at time 1, 0.84 respectively 0.71 at time 2 and 0.69 respectively 0.62 at time 3 are represented (Mauno et al., 2001). Considering construct validity, the factor loadings for the unidimensional measure range between 0.65 and 0.87. A factor loading thereby represents the correlation between an item and a corresponding factor. Therefore, factor loadings vary between -1 and 1. The classification of factor loadings corresponds to those of correlations in general. Values smaller than ± 0.10 are classified as minor. Values greater or equal than ± 0.10 and smaller than ± 0.30 are considered as small. Values greater or equal than ± 0.30 and smaller than ± 0.50 are classified as moderate and values greater or equal than ± 0.5 are considered as large (Cohen, 1988; Cohen et al., 2003). For the dimension job importance of the multidimensional measure the factor loadings are varying between 0.22 and 0.93. For the dimension powerlessness, factor loadings between 0.54 and 0.73 could be found (Mauno et al., 2001).[17] The results are presenting similar or even higher values for the unidimensional job insecurity scale than for the tested multidimensional measure leading Mauno et al. (2001) to recommend the use of an unidimensional job insecurity measure for further research.

Furthermore, Reisel and Banai (2002) examine the multidimensional measure considering qualitative and quantitative job insecurity and find out that multidimensional measures do not add any amount of explanatory power to the measurement of job insecurity. They examine the relationship between job insecurity and commitment, trust and job search behavior using regression analysis for a sample of 276 managers in the United States of America (USA)

[17] The last dimension, job loss probability, can however not be examined further, because it turned out that the models do not satisfactorily fit the data (Mauno et al., 2001).

(Reisel and Banai, 2002). Thereby, in order to measure job insecurity, they use the Job Insecurity Scale by Ashford et al. (1989) as multidimensional measure and an unidimensional measure of job insecurity by Caplan and Jones (1975) consisting of four items (Reisel and Banai, 2002). The results support the use of an unidimensional measure by showing, that in terms of the outcome variables commitment and trust, the global measure of job insecurity explains even more variance in the corresponding outcome variable than the multidimensional measure does (Reisel and Banai, 2002).

Therefore, taking into account the derived unidimensional definition of job insecurity,[18] the criticism of multidimensional measures and recommendation for unidimensional measures pointed out by Probst (2003) and Vander Elst et al. (2014) as well as the empirical evidence presented by Reisel and Banai (2002) and Mauno et al. (2001), unidimensional measures will be pursued further. More detailed, unidimensional multi-item measures and unidimensional single-items measures are considered (Figure 1).

One of the first unidimensional, multi-item measure is the measure of job insecurity developed by Caplan and Jones (1975). The scale consists of four items which are questioned using a 5-point response format (Caplan and Jones, 1975). The internal consistency of the scale is indicated with a Cronbach's α value of 0.73 in a study by Ashford et al. (1989) for the USA. De Witte (2000) develops an unidimensional, multi-item measure of job insecurity using four items rated on a 5-point Likert scale. Indexing is used to determine job insecurity after data collection through the different items (De Witte, 2000). Vander Elst et al. (2014) examine the reliability with the meaning of internal consistency, the construct validity and the criterion validity for this measurement in five different European samples.[19] Cronbach's α values for job insecurity are identified to range between 0.82 and 0.88 for the different samples and is stated with 0.82 for the total sample, indicating internal consistency.[20] Construct validity is examined using singlegroup and multigroup CFA. The results show significant item loadings, ranking between 0.66 and 0.85 for the different items and different samples in the singlegroup CFA and good model fits for the singlegroup and for the multigroup CFA (Vander Elst et al., 2014). The criterion validity is tested by examining the relation between job insecurity and affective organizational commitment, perceived general health and

[18] See Chapter 2.1.1.

[19] Vander Elst et al. (2014) use a Belgian sample ($N = 377$), a Dutch sample ($N = 394$), a Spanish sample ($N = 516$), a Swedish sample ($N = 310$) and a British sample ($N = 369$).

[20] Cronbach's α amounts to 0.85 for the Belgian sample, 0.88 for the Dutch sample, 0.87 for the Spanish sample, 0.82 for the Swedish sample and 0.88 for the British sample (Vander Elst et al., 2014).

self-reported performance (Vander Elst et al., 2014). Relations between job insecurity and all these three indicators could be found more or less in all subsamples as well as in the total sample (Vander Elst et al., 2014).[21]

A further example for an unidimensional multi-item measure of job insecurity is a part of the Work Opinion Questionnaire developed by Johnson et al. (1984). The questionnaire was developed to measure job-related attitudes including job security and hence the absence of job insecurity. The final version of the questionnaire consists of seven items for job security which are questioned with five response options (Johnson et al., 1984). After data collection, job security and hence the absence of job insecurity is determined by indexing over the seven items (Johnson et al., 1984). The Cronbach's α value is stated with 0.75 in the original research (Johnson et al., 1984). This indirect measurement of job insecurity by job security is possible as long as job insecurity and job security are assumed to represent the extreme forms of one continuum and the relationship, that no job security equals job insecurity and that no job insecurity equals job security, are assumed to exist (Virtanen et al., 2002).

In contrast to unidimensional multi-item measures, unidimensional single-item measures only consist of one item. This single-item is often a question concerning the perceived probability of loosing a job (e.g. De Witte (1999); Mohr (2000); Probst and Jiang (2017) or Green (2011) based on the Household, Income and Labour Dynamics in Australia Survey (HILDA), Burgard et al. (2012) based on the Michigan Recession and Recovery Study (MRRS) and Lam et al. (2015) based on the Work, Family & Health Network Study (WFHN)). In contrast of asking about the perceived probability, some studies also use more intuitive questions asking for concerns about the security of a job directly (e.g. Clark et al. (2010), Knabe et al. (2010), Geishecker (2012) or Otterbach and Sousa-Poza (2016) based on the GSOEP[22]). This again presents an indirect elaboration of job insecurity by job security, which is possible, when it is assumed that job security and job insecurity are the extreme forms of one continuum (Johnson et al., 1984; Sverke et al., 2002; Virtanen et al., 2002). In line with this, other studies use questions which ask to rate a statement about poor security like in the Effort-Reward Imbalance (ERI) at work questionnaire by Siegrist (1996)[23] (e.g. Anderson and Pontusson (2007); Erlinghagen (2008);

[21] Based on the unidimensional multi-item measure by De Witte (2000) and the multidimensional measures by Ashford et al. (1989) and Hellgren et al. (1999), Sverke et al. develope a 5-item unidimensional, multi-item measure in 2004. For more information see Sverke et al. (2004).

[22] A similar measure of job insecurity can be found in the Russian Longitudinal Panel Survey (RLMS).

[23] A short version of the ERI at work questionnaire can be found in Siegrist et al. (2009).

Debus et al. (2012); Probst and Jiang (2017)). A similar method can be found in Caverley et al. (2007). They ask to rate a statement about the worries considering job security to measure job insecurity. Arnold and Feldman (1982) and Preuss and Lautsch (2002) however measure job insecurity by asking, how likely it is that the respondent will be fired or loose a job. Another example for an unidimensional single-item measure is the question about the satisfaction with job security, which can be found in Finegold et al. (2002) or in Clark and Postel-Vinay (2009), using the European Community Household Panel Survey (ECHP).[24]

It appears that, next to a large part of authors, also the most household panels (e.g. GSOEP, British Household Panel Survey (BHPS), HILDA, ECHP or RLMS) or other large surveys (e.g. WFHN, MRRS or the Whitehall II study) use unidimensional, single-item measures to elaborate job insecurity.[25] Single-item measures of course offer the possibility to elevate job insecurity without substantially extending a questionnaire and are therefore often used in large surveys. However, a study by Sverke et al. (2002) shows that single-item measures tend to underestimate the relationship between job insecurity and an outcome variable, which should be considered while using single-item measures. Additionally, it is obvious that single-item measures collect less data than multi-item measures. In literature and empirical research, there is no prevailing opinion about unidimensional measures using multi-items or using single-items. Depending on whether more importance should be given to the practicability or the number of information collected, unidimensional measures using single-items or using multi-items should be used.

For the following analysis, the data of the GSOEP is used, where job insecurity is elaborated by a single-item measurement. Thereby, the detection of job insecurity in the GSOEP refers to job insecurity as concerns about job security. Hence, the job insecurity measurement occurs indirectly. If an individual reports to be concerned about job security, this individual is categorized of suffering from job insecurity. This relation exists under the assumption of job insecurity as one continuum with the extreme forms, completely job insecure and completely job secure. The single-item measurement is therefore in line

[24] The question concerning satisfaction with job insecurity does not match with any of the definitions of job insecurity in Chapter 2.1.1. Therefore, it is possible that this way of measurement does not capture job insecurity as it is understood in the present thesis. To present a full picture of different measurements, it is still mentioned here, but will not be pursued further.

[25] An overview of studies using multidimensional, unidimensional multi-item or unidimensional single-item measures can be found in Sverke et al. (2002) and Keim et al. (2014). A list of large surveys using unidimensional single-item measures is presented by Virtanen et al. (2013).

with the underlying definition of job insecurity, as the subjective concern about the permanence of a job, for the present thesis.

2.2 Mental Health

2.2.1 Definition

Mental health is an important aspect of health in general, which is shown by the definition of general health given by the World Health Organization (WHO), as „a state of complete physical, mental and social well-being and not merely the absence of disease or infirmity“ (WHO, 2014). Mental health is thereby further defined as „a state of well-being in which the individual realizes his or her own abilities, can cope with the normal stresses of life, can work productively and fruitfully, and is able to make a contribution to his or her community“ (WHO et al., 2004). The definition of the WHO displays three different dimensions of mental health. The first dimension is *well-being*, the second one is the *effective functioning of an individual* and the third dimension is the *effective functioning of this individual for a community* (Westerhof and Keyes, 2010).

The first dimension, *well-being*, is not uniformly defined in literature and will hence be presented in more detail (Westerhof and Keyes, 2010). Well-being can be distinguished in hedonic well-being and eudaimonic well-being (Waterman, 1993; Ryan and Deci, 2001; Keyes et al., 2002; Deci and Ryan, 2008; Westerhof and Keyes, 2010; Disabato et al., 2016). Hedonic well-being, also called emotional well-being, refers to overall satisfaction, happiness, serenity, interest in life as well as experience of positive emotional states (Keyes, 2007; Westerhof and Keyes, 2010; Disabato et al., 2016). Eudaimonic well-being however focuses on optimal functioning and the presence of meaning and development of an individual's potential (Keyes, 2007; Disabato et al., 2016). Eudaimonic well-being itself can be distinguished again in psychological well-being and social well-being (Keyes, 2007). Thereby, psychological well-being is the subjective evaluation of psychological functioning, referring to an individual's own potential and hence to the second dimension of the WHO definition. Social well-being is referred to the subjective evaluation of social functioning which means the functioning of an individual in relation to her respectively his social engagement and societal involvement and hence in line with the third dimension of the WHO definition (Westerhof and Keyes, 2010). Based on this definition of well-being, mental health can be understood as a combination of hedonic and eudaimonic well-being (Westerhof and Keyes, 2010).

Keyes (2002) identifies a fourth dimension, which is essential for mental health.

This dimension is called vitality. Vitality is defined as a feeling of energy, enthusiasm and aliveness (Ryan and Frederick, 1997; Bostic et al., 2000; Ryan and Deci, 2008).[26] Combining this dimension with those identified by the WHO, mental health consists of four dimensions - *emotional well-being*, *psychological functioning*, *social functioning* and *vitality*. For an encompassing definition of mental health, all dimensions are included and mental health is defined as a state of emotional well-being, psychological functioning, social functioning and vitality. Following the definition of the WHO and including the work of Ware et al. (1996), Keyes (2002) and Westerhof and Keyes (2010), mental health can be defined for further understanding in the present analysis as follows: *Mental health is defined as a state of well-being in which the individual realizes his or her own abilities, can cope with the normal stresses of life, can work productively and fruitfully, is able to make a contribution to his or her community, experiences positive emotional states and feels full of energy.*

2.2.2 Measurement

Of course, mental health can be diagnosed by a medical examination. For empirical research however, such a measurement is not at least inadequate against the background of medical confidentiality and patent's privacy. Consequently, researchers use subjective statements to get information about the mental health status of individuals and developed diverse questionnaires to capture mental health (McDowell, 2006). These questionnaires can be divided into two groups: questionnaires measuring the mental health status as such and questionnaires that measure mental health within general health and quality of life (McDowell, 2006).[27]

An example of the group of questionnaires, measuring mental health as such is the General Health Questionnaire (GHQ), developed in 1972 by Goldberg. It represents a self-administered screening tool to identify individuals, which are likely to develop a psychiatric disorder (McDowell, 2006; Jackson, 2007). The GHQ is not only one of the first questionnaires that has been developed, but also one that is most often used and recommended in the group of questionnaires measuring mental health as such (McDowell, 2006; Jackson, 2007). It is often applied, especially in occupational research and not at least, because it is easy to complete by individuals and easy to score by researchers (Jackson,

[26] Ryan and Frederick (1997) additionally argue that vitality also refers to physical health. Due to the focus of this thesis on mental health, this point of view is however not pursued further.

[27] This chapter only presents the questionnaires of both groups, which are used most frequently, since a high number of questionnaires exists. For an overview see McDowell (2006).

2007).[28] The GHQ is available in 38 different languages and diverse versions, each with a different number of items. There exists a 60-item, a 30-item, a 28-item and a 12-item version in which the 12-item version, the GHQ-12, is nowadays the most popular one (Werneke et al., 2000; McDowell, 2006; Jackson, 2007; Romppel et al., 2013). The response options for the GHQ-12 are frequency scales ranking, depending on the corresponding item, for example from „less than usual“ to „much more than usual“ (McDowell, 2006).

Originally, the GHQ-12 was developed as an unidimensional scale, but diverse studies however find a two- or three-factor solution.[29] Until now, it is not fully confirmed, if the GHQ-12 measures different dimensions of mental health or, if it is an unidimensional scale (Romppel et al., 2013). The dimensionality as well as the reliability and validity of the GHQ-12 have been proved in several studies and in different languages.[30] Schmitz et al. (1999) for example evaluate the reliability, validity and factor analysis of the GHQ-12 for Germany. Thereby, reliability is conducted using internal consistency which is stated with a Cronbach's α value of 0.91 for a sample of 421 German adults. The 421 adults fulfilled the GHQ-12 and were diagnosed additionally by a mental health professional. Therefore, validation is conducted by Schmitz et al. (1999) using Receiver Operating Characteristic (ROC) analysis. A ROC analysis is a method to evaluate the accuracy of a diagnostic test by plotting the sensitivity against the specificity (ROC-Curve). Whereas sensitivity describes the probability of correct positive results. Specificity however represents the probability of correct negative identified results (Hajian-Tilaki, 2013; Backhaus et al., 2016). To validate the ability to identify correct positive and correct negative cases of a specific test, the Area Under Curve (AUC) can be calculated. AUC is thereby a value between 0.5 an 1, while 1 represents a perfect attribution. An AUC value which is smaller than 0.7 is classified as insufficient. AUC values greater or equal 0.7 and smaller than 0.8 are classified as

[28] In the original scoring method by Goldberg, the items are scored 0-0-1-1, but also the Likert method (0-1-2-3) and the C-GHQ method (health items: 0-0-1-1, illness items: 0-1-1-1) are possible (Goldberg et al., 1997). For a comparison of the different methods see Goldberg et al. (1997).

[29] For example, Gureje (1991), Politi et al. (1994), Werneke et al. (2000), Picardi et al. (2001), Schmitz et al. (2001), Kalliath et al. (2004), Vanheule and Bogaerts (2005) and Toyabe et al. (2007) find a two-factor solution. Graetz (1991), Bun Cheung (2002), Campbell et al. (2003), French and Tait (2004) and Shevlin and Adamson (2005) however find a three-factor solution.

[30] Examples are Pevalin (2000) or Hankins (2008) for England, Sánchez-López and Dresch (2008) for Spain, Makowska et al. (2002) for Poland, Piccinelli et al. (1993) or Politi et al. (1994) for Italy. Goldberg et al. (1997) for 15 citys including Ankara, Athens, Bangalore, Berlin, Groningen, Ibadan, Mainz, Manchester, Nagasaki, Paris, Rio de Janeiro, Santiago, Seattle, Shanghai and Verona. For more examples see Goldberg et al. (1997) or McDowell (2006).

acceptable. AUC values greater or equal 0.8 and smaller than 0.9 are classified as excellent and values greater than 0.9 are classified as extraordinarily (Backhaus et al., 2016). In the study by Schmitz et al. (1999), displaying the ROC curve, the AUC is stated with 0.76. Sensitivity, i.e. the probability to identify a person who is mentally ill as such and specificity, i.e. the probability to identify a healthy person as healthy is found to be 0.70 respectively 0.68 (Schmitz et al., 1999). Thereby, the positive predicted value is 0.56 and the negative predicted value 0.8 (Schmitz et al., 1999). The implementation of the factor analysis displays a two-factor structure (Schmitz et al., 1999). Another study by Romppel et al. (2013) tests the dimensionality of the 12-item version for Germany and compares an unidimensional, a two-factor and a three-factor solution based on a representative population sample. In the study by Romppel et al. (2013), the unidimensional version represents the best overall fit for the used data .[31]

The most famous and widely used questionnaire in the group of questionnaires that measure mental health within general health and quality of life is the 36-Item Short-Form Health Survey (SF-36). Mental health is represented by the Mental Component Summary Scale (MCS) within the SF-36 or within the shorter version, the 12-Item Short-Form Health Survey (SF-12) (Müller-Nordhorn et al., 2004; Morfeld et al., 2005; Erhart et al., 2006).[32] The SF-36 respectively the SF-12 are developed within the Medical Outcome Study (MOS) which was a study, observing patients with chronic conditions over two years to examine how components of the health care system are related to the outcomes of care in America, starting 1960 (Tarlov et al., 1989). The core survey in the MOS consists of 116 items measuring health-related quality of life in terms of physical health, mental health and health in general. On that basis, the short version of 36 items was developed and in 1995 also the even shorter version of 12 items (Tarlov et al., 1989).

Health-related quality of life is the subjective evaluation of social, psychological and physical well-being and functioning (Bullinger, 2000). The SF-36, as well as the SF-12, capture eight dimensions which can be aggregated to the summary measures MCS and the Physical Component Summary Scale (PCS) (Ware et al., 1996, 1998; Bullinger, 2000; Gunzelmann et al., 2006). The MCS consists of the subscales *vitality*, *social functioning*, *role-emotional* and *men-*

[31] Other examples of questionnaires measuring mental health as such are the Health Opinion Survey or the Health Perception Questionnaire. For an overview see McDowell (2006).

[32] Additional questionnaires, developed from the SF-36 are the SF-6D and the SF-8. For more information see e.g. Walters and Brazier (2003) for the SF-6D and e.g. Ellert et al. (2005) for the SF-8.

tal well-being (Ware et al., 1996, 1998; Gunzelmann et al., 2006). *Vitality* refers to the extent of feelings of energy or of exhaustion. *Social functioning* captures how mental or physical health impair normal social activities and *role-emotional* however captures the extent to which emotional problems impair work or other daily activities. *Mental well-being* finally refers to the extent of experiences in mental impairment (Ware et al., 1996, 1998; Bullinger, 2000; Gunzelmann et al., 2006). The subscale of the SF-36, *mental well-being*, is also used independently of the total SF-36 and known as Mental Health Inventory (MHI-5) (Ware et al., 1996, 1998).[33] The PCS consists of the subscales *physical functioning*, which refers to the extent of the impairment of physical activities and *role physical*, capturing how physical health impairs work or other daily activities. Additionally, it consists of the subscales *physical pain*, which refers to the extent of physical pains and their effects of daily activities and *general health*, which means the subjective evaluation of own health (Ware et al., 1996, 1998; Bullinger, 2000; Gunzelmann et al., 2006).

The number of items per summary scale in the SF-12 and the SF-36 are displayed in Table 1. The first column of Table 1 displays the given concept. The second column expresses the appropriate summary scale, the PCS or the MCS, if a certain summary scale corresponds to the concept in column 1. Column 3 of Table 1 displays the number of items of the given concept in the SF-12, column 4 accordingly the number of items of the given concept in the SF-36. In the SF-36, the MCS and the PCS together comprise 35-items and one additional item captures the change of health (Ware et al., 1998). In the SF-12, however the PCS and the MCS comprise together 12-items. Thereby, it is to be mentioned that in the SF-12 in each case, two concepts, which are aggregated to MCS or PCS, are represented by two items and the other two concepts are each represented by one item. This results in the fact that mental health (MCS) is measured with six items representing four subscales of mental health. The response options to the different items are varying independently of the dimensions from „yes“ and „no“ to intensity scales with 5 to 6 response options (Ware et al., 1998).

[33] The reliability and validity of the MHI-5 are verified by several empirical studies (e.g. McCabe et al. (1996), Rumpf et al. (2001), Strand et al. (2003), Friedman et al. (2005)). For the use of mental health questionnaires in everyday primary care, cut-off values are implemented (Rumpf et al., 2001). In the comparison of the MHI-5 and the SF-36 using cut-off values, the MHI-5 is found to detect mental disorder more accurate than the SF-36 (Kelly et al., 2008). Nevertheless, as the MHI-5 only concentrates on one subscale of the MCS, the MHI-5 should not be pursued further.

Table 1: SF-12 vs. SF-36 – Number of Items

Concept	Summary Scale	SF-12	SF-36
Physical functioning	PCS	2	10
Role physical	PCS	2	4
Physical pain	PCS	1	2
General health	PCS	1	5
Vitality	MCS	1	4
Social functioning	MCS	1	2
Role-emotional	MCS	2	3
Mental well-being	MCS	2	5
Change in health	–	0	1
Overall	–	12	36

Source: Own presentation according to Ware et al. (1998).

To score the MCS and the PCS of the SF-36 respectively of the SF-12 the individual items have to be aggregated to the corresponding eight subscales. This is done by scoring each item on a range from 0 to 100, whereas 0 represents the lowest possible score and 100 the highest possible score (Ware et al., 1993). After that, the items of each scale are averaged together to the corresponding eight subscales (Ware et al., 1993). For this procedure, all items have to be scored so that a high score means a better health status (Ware et al., 1993).

After creating the eight subscales, the scoring of the MCS and the PCS comprises three steps. In a first step, the eight scales are z-standardized (mean = 0, standard deviation = 1) using the means and standard deviations from a general population database of the corresponding country (Ware et al., 1994; Ellert and Kurth, 2004). Thereby, the z-score standardization is carried out by subtracting the mean from each subscale score and dividing the difference by the corresponding standard deviation from the general population database.[34] In a next step, the eight subscales are weighted with factor score coefficients, which are determined using EFA for the general population database of the corresponding country (Ware et al., 1994; Ellert and Kurth, 2004). Then, the weighted subscales are summed up to a component score for the corresponding component summary, MCS and PCS (Ware et al., 1994; Ellert and Kurth, 2004). In a last step, a T-score transformation of the component scores is carried out to receive a mean of 50 and a standard deviation of 10 (Ware et al., 1994; Ellert and Kurth, 2004). It results in a single value for the MCS and

[34] The scales of the original SF-36 are standardized using the general USA population (Ware et al., 1994).

for the PCS, measuring the mental health status and respectively the physical health status, whereas a higher score represents a better mental health, respectively physical health status (Ware et al., 1994; Ellert and Kurth, 2004).

After the development of the SF-36 and the SF-12, both surveys were revised in 1996 to generate a better understanding and ensure better intercultural comparability (Jenkinson et al., 1999; Ellert and Kurth, 2013). Hence, today also second versions of both surveys exist. Version 2 of the SF-36, the SF-36v2 differs from version 1 on the one hand in more precise wording. Thereby, eleven items are reworded. On the other hand, the response options of the items corresponding to the scales role-physical, role-emotional, vitality and mental well-being are adjusted (Morfeld et al., 2005; Lam et al., 2013). The response options for the scales role-physical and role-emotional have thereby been extended from 2 to 5 options. The response options for the scales, vitality and mental well-being have however been reduced from 6 to 5 options (Morfeld et al., 2005). The second version of the SF-12, the SF-12v2 also differs in item wording. Here, two items are reworded. Additionally, the response options of the items corresponding to the scales role-physical, role-emotional, vitality and mental well-being are also adjusted (Morfeld et al., 2005). Also here, the response options for the scales role-physical and role-emotional have been extended from 2 to 5 options and the response options for the scales vitality and mental well-being have been reduced from 6 to 5 options (Morfeld et al., 2005). The first version as well as the second version of the SF-36 have shown to be reliable and valid measures across general population, specific patient groups and also in different languages (e.g. Brazier et al. (1992); Jenkinson et al. (1994); Failde et al. (2000); Gunzelmann et al. (2006)). The original version of the SF-36 and the SF-12 is in English, but there exists a set of rules for translating, psychological testing and the standardization of the survey in other languages provided by the International Quality of Life Assessment (IQOLA) Project Group, which was found to support the international use of the SF-36/SF-12 (Bullinger, 2000).[35]

Morfeld et al. (2011) present the reliability and validity for the German version of the SF-36v1 for a representative population sample and various other samples like students, patients with heart diseases, patients with back pain or diabetes (Morfeld et al., 2011). The majority of the Cronbach's α values of the different scales and for the different samples are found to be above 0.7, showing

[35] For more information on the IQOLA Project, see Aaronson et al. (1992).

generally internal consistency of the SF-36v1.[36] Convergent validity is examined by determining the correlation of the SF-36 with the Nottingham Health Profile (NHP)[37] and the EuroQol EQ-5D Quality of Life Scale (EQ-5D)[38] (Morfeld et al., 2011). Thereby, correlations between scales, which are similar in terms of content, ranking from 0.47 to 0.78 respectively 0.44 to 0.75 (Morfeld et al., 2011). The examination of the discriminant validity shows a great differentiability between patient groups, which are classified by means of clinical criteria (Morfeld et al., 2011). Additionally, the construct validity is examined by Morfeld et al. (2011) using CFA. The results show high correlations of the associated items with the respective scales. On average the scale-fits are found to be between 95% and 100% (Morfeld et al., 2011).[39]

The reliability and validity of the second version of the SF-36 in comparison to the first version are examined for Germany by Morfeld et al. (2005).[40] More detailed, Morfeld et al. (2005) test the internal consistency using Cronbach's α and the construct validity using scale fits. Their results show values for Cronbach's α for all scales above 0.8 and for physical functioning, role physical and role-emotional even above 0.9 (Morfeld et al., 2005). Considering construct validity, Morfeld et al. (2005) show scale fits of 97.5% of the general health and mental well-being scales and even scale fits of 100% for the remaining six scales (Morfeld et al., 2005). Comprehensively, Morfeld et al. (2005) determine that the first and the second version of the SF-36, for a great extent are psychometrically and textually equal.

The SF-12 respectively the SF-12v2 is additionally proved to be a plausible and practicable alternative to the SF-36 respectively the SF-36v2 (Ware et al., 1996, 1998; Lam et al., 2013) as it shows similar levels of precision in deriving

[36] The Cronbach's α for the general health scale only achieves values between 0.57 and 0.69 in the sample of student, healthy parents, patients with heart valve replacement, patients with hypertension and diabetics. The social functioning scale accomplishes a Cronbach's α value of only 0.64 in the sample of patients with hypertension (Morfeld et al., 2011).

[37] The NHP is a self-reporting questionnaire to measure subjective health in terms of physical, social and emotional health, which was developed and validated in the end of the seventies in Great Britain (Hunt et al., 1985). The German version of the NHP was validated in 1997 by Kohlmann et al.

[38] The EQ-5D is a self-completed questionnaire measuring quality of life and expressing the individual health status in a single number. It was developed in 1987 by the International European Quality of Life Group (Rabin and de Charro, 2001; McDowell, 2006). A validation of the German version can be found in Hinz et al. (2006).

[39] Further results for Germany can be found in Gunzelmann et al. (2006). Similar results for England can be found in Brazier et al. (1992). For an overview of various studies examining validity and reliability of the SF-36v1 see Ware et al. (1998).

[40] The U.S. version is examined by Ware et al. (2000). For England the performance of the SF-36v2 is documented by Jenkinson et al. (1999). Taft et al. (2004) examine version 2 of the SF-36 for Sweden.

the MCS and the PCS (Jenkinson et al., 1997; Gandek et al., 1998; Ware et al., 1998; Bullinger, 2000). For Germany, the correlation between the PCS of the SF-36 and the PCS of the SF-12 amounts to $r = 0.96$ and the correlation between the MCS of the SF-36 and the MCS of the SF-12 to $r = 0.94$ (Morfeld et al., 2011).[41]

Today, both versions are still used and there is no clear preference for one of the versions (Morfeld et al., 2005), but the MCS and the PCS of the 12-item version are even more often used than those of the 36-item version, not at least because of its shortness (Ware et al., 1998). The 36-item version can on average be completed within ten minutes, the 12-item version however can on average be completed within two minutes (Morfeld et al., 2011). The 12-item version offers a compromise between high practicability and precise measurement (Morfeld et al., 2011). Although the reliability deteriorates because of the reduced number of items, this is negligible in large samples and it is hence recommended above all for samples with more than 500 observations (Morfeld et al., 2011).[42]

Considering the multidimensional definition of mental health which was devised in Chapter 2.2.1, it is also useful to measure the mental health status in the following analysis with a multidimensional measurement of mental health. The multidimensional measure of the SF-36 and of the SF-12 is thereby appropriate concerning the accordance of the dimensions with the underlying definition. Additionally, using the GSOEP the 12-item version is appropriate as a sample of more than 500 observations can be achieved and hence the advantage of high practicability can be exploited. Therefore, considering the following analysis, the mental health status is measured using the MCS based on the 12-item version, included in the GSOEP. Whereas the measurement of the mental health status of an individual in the GSOEP is based on the SF-12v2.

[41] Similar values of correlations for Germany can be found in Müller-Nordhorn et al. (2004) or Haibel et al. (2004). For the USA a correlation between the PCS of the SF-36 and the PCS of the SF-12 was found by Ware et al. (1998) to be $r = 0.951$. The correlation between the MCS of the SF-36 and the MCS of the SF-12 was found to be $r = 0.969$ (Ware et al., 1998). A direct comparison of the SF-12v2 and the SF-36v2 is until now only available for China. See Lam et al. (2013).

[42] Further questionnaires measuring mental health within general health and the quality of life are the previously mentioned NHP and the EQ-5D as well as the Physical and Mental Impairment-of-Function Evaluation and the Quality of Life Index. For an overview see McDowell (2006).

3 Theoretical Foundation

3.1 The Spillover-Crossover Model

The Spillover-Crossover Model was developed by Bakker and Demerouti in 2013, bringing together the literature on spillover and on crossover. Spillover and crossover are two different ways for the transmission of experiences (Bolger et al., 1989; Wethington, 2000; Westman, 2001). The intra-individual transmission from one life domain of an individual to another life domain of this individual is called spillover and represents a within-person across-domains process (Westman, 2001; Bakker and Xanthopoulou, 2009; Bakker and Demerouti, 2013). A crossover however is represented by a transmission of experiences across individuals and is hence a dyadic, inter-individual process. A crossover usually takes place between individuals who are closely related or who are in the same social environment (Westman, 2001; Bakker and Xanthopoulou, 2009).

The Spillover-Crossover Model focuses on transmissions from the work-domain to the home-domain of an individual.[43] Hence, the Spillover-Crossover Model deals with the spillover of work-related experiences from the work-domain to the home-domain of individuals followed by the crossover of these work-related experiences as well as its consequences between individuals in the same home-domain (Bakker and Demerouti, 2013).

The Spillover-Crossover Model is based on the Job Demands-Resources Model, developed by Demerouti et al. (2001). Like in the Job Demands-Resources Model, for the Spillover-Crossover Model it is also assumed that a job can be expressed by different job characteristics. These characteristics can be subdivided into job demands and job resources (Bakker and Demerouti, 2013). Job demands are characteristics of a job that call for physical or mental effort and cause physiological and psychological cost like exhaustion or burnout (Demerouti et al., 2001). Examples for job demands are time pressure, workload, noise or mentally distressing situations. Job resources however are job characteristics helping to deal with job demands. Job resources can be physical, psychological, social or organizational aspects supporting to achieve work goals, reducing costs arising because of job demands and stimulating personal development and growth (Demerouti et al., 2001). Examples for job resources are autonomy, social support or performance feedback (Bakker and Demerouti, 2013). Considering the Job Demands-Resources Model, job demands may lead

[43] Transmissions from the home-domain to the work-domain are also assumed but not pursued further by Bakker and Demerouti (2013).

to burnout whereas job resources may cause engagement (Bakker and Demerouti, 2013). The expression of job demands and job resources of a certain job constitute work-related experiences, which thus can either be positive or negative and hence lead to positive or negative spillover and crossover.

The Spillover-Crossover Model by Bakker and Demerouti (2013) is represented in Figure 2 including positive as well as negative spillover and crossover. The upper part of Figure 2 represents the processes of spillover and crossover for men and the lower part the processes of spillover and crossover for women. Due to this way of presentation, the crossover between partners can easily be displayed.[44] It can be seen that the transmission process including spillover and crossover typically starts in the work-domain which is displayed in the left part of Figure 2. Furthermore, it is shown that the spillover process is upstream of the crossover process (Bakker and Demerouti, 2013).

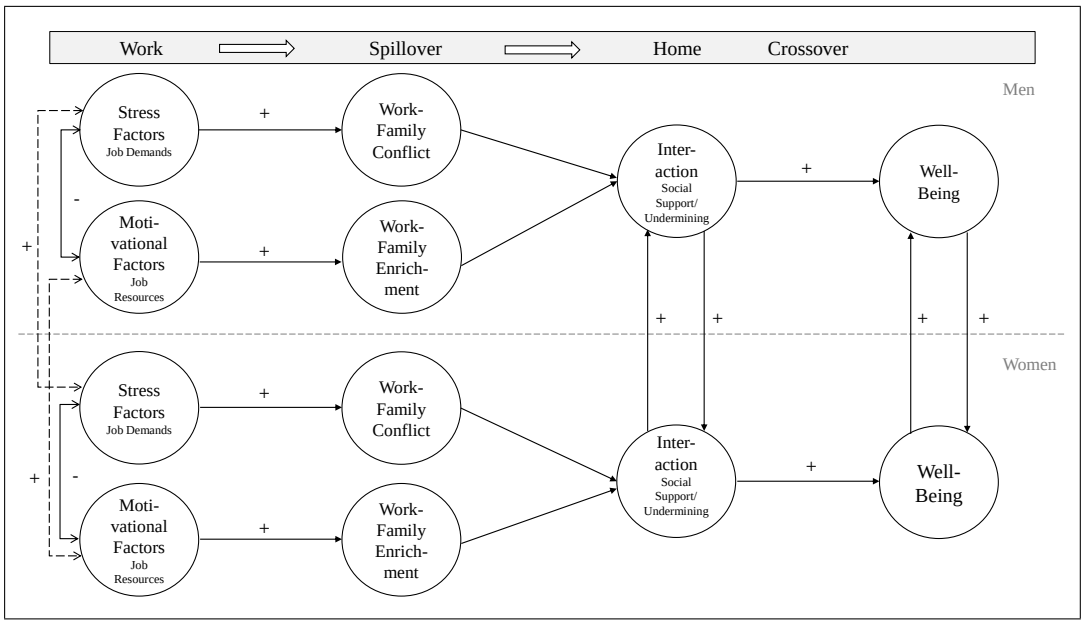

Figure 2: Spillover-Crossover Model
(Source: Own presentation according to Bakker and Demerouti (2013).)

Job demands which are assumed to cause strain, spill over to the home-domain and lead to a work-family conflict (Bakker and Demerouti, 2013). A work-family conflict is established in role theory. Role theory is not a uniform theory, but rather a collective term for different theory interpretations, concepts

[44] Of course, the Spillover-Crossover Model can also be transferred to same-sex couples. Here, it should be focused on the genuine model by Bakker and Demerouti (2013) with heterosexual couples. Furthermore, homosexual couples are not pursued, because on the basis of the available data a consideration of homosexual couples is not expedient. An example for an examination of spillover and crossover effects in same-sex couples can be found in Totenhagen et al. (2017).

or views about individual behavior and expectations concerning individual behavior in society. It implies that each individual in a society has expectations about her respectively his own behavior as well as expectations about the behavior of other members within the same society. According to this, a role is in general defined as a cluster of socially shared expectations or beliefs about individual behavior in a certain position or in a particular category (Solomon et al., 1985; Eagly et al., 2000). For each individual, it is assumed that it holds different roles which are associated with requirements about how individuals should behave (Biddle, 1986). Each role therefore generates different requirements for an individual. Important roles of an individual are the family role and the work role. Derived from the definition of *role*, a family role can be defined as a cluster of socially shared expectations about an individual as a family member. A work role however can be defined as a cluster of socially shared expectations about an individual at the workplace (Solomon et al., 1985; Eagly et al., 2000).

A work-family conflict therefore arises, if there are aspects in the work-role that lead to problems concerning the participation in the family-role and make it incompatible to fulfill both roles. Participation in one role leads to problems with the participation in the other role (Katz and Kahn, 1978; Greenhaus and Beutell, 1985). A reason for such a work-family conflict can be the time demand of one role, which makes it difficult to fulfill the other role. A further reason can arise by a certain behavior which may be attached to one of the roles but however not in the other role. Finally, a reason is the transmission of stress from one role to the other role (Greenhaus and Beutell, 1985).[45] An example for such a spillover from the work-domain to the home-domain is an individual, who is pressed for time at work and is still tense at home.

The spillover is followed by a crossover, which can either be direct or indirect (Bakker and Demerouti, 2013). Crossover is demonstrated in the right part of Figure 2. A direct crossover means a crossover of strain to a partner through the well-being status of the other partner and hence a direct crossover of well-being between partners (Bakker and Demerouti, 2013). Such a direct crossover is assumed to occur because of empathic identification (Bakker and Xanthopoulou, 2009). The strain of an individual leads to an empathic reaction of the partner which triggers an increase in the strain level of this partner (Bakker and Xanthopoulou, 2009). It shows that crossover particularly happens between individuals, who pay close attention to each other and who

[45] Next to the work-family conflict, also a family-work conflict can arise. The family-work conflict is given, if aspects in the family-role lead to problems concerning the participation in the work-role (Netemeyer et al., 1996).

define themselves as interrelated, rather than as independent from each other (Bakker and Xanthopoulou, 2009). The direct crossover is associated with the Theory of Emotional Contagion by Hatfield et al. (1993) (Bakker and Demerouti, 2013). Hatfield et al. (1993) define the tendency to mimic expressions of other individuals as emotional contagion. Thereby, this tendency arises automatically and synchronizes the facial, vocal and postural expressions of other individuals they interact with. Furthermore, the synchronized facial, vocal and postural expressions lead to an immediate subjective emotional experience due to neuronal feedback. This means, that the emotional experiences of other individuals are empathized, because of the synchronization of the facial, vocal and postural expressions (Hatfield et al., 1993).

Considering an indirect crossover, the work-family conflict which arises because of a strain spillover, is assumed to have a negative impact on the interaction at the home-domain, which then effects the partner's well-being (Bakker and Demerouti, 2013). In the Spillover-Crossover Model, it is assumed that the strain spillover leads to social undermining or a lack of social support in the interaction between partners followed by reduced well-being. Social undermining is defined as behaviors, which display anger or dislike towards a certain person, criticism towards the person's attributes, actions or efforts as well as behaviors which hinder this person (Vinokur and Van Ryn, 1993). A lack of social support however means a lack of affection, recognition, affiliation, information and practical and material assistance (Vinokur and Van Ryn, 1993; Bakker and Demerouti, 2013). Indirect crossover can be assumed to arise due to group behavior, when crossover is traced back to the Social Identity Theory by Tajfel and Turner (1979). The Social Identity Theory fundamentally deals with the role of self-conception and social beliefs about group processes and relations within groups and tries to explain cognitions and behavior due to group processes (Tajfel and Turner, 1979; Trepte, 2013; Hogg, 2016). Following the Social Identity Theory, individuals display group behavior, like solidarity with the own group and discrimination against other groups, as a part of the social identity process. Such group behavior is thereby demonstrated to achieve positive self-esteem and self-enhancement and is based on three mental processes of individuals: the social categorization, the social identification and the social comparison (Tajfel and Turner, 1979; Trepte, 2013; Hogg, 2016). The social categorization describes the categorization of individuals into groups to identify themselves and structuring social interaction. This categorization is followed by the social identification, in which individuals categorize themselves as belonging to a specific group. In the final process, social comparison to other groups occurs and group behavior arises to improve self-esteem and self-

enhancement (Tajfel and Turner, 1979; Trepte, 2013; Hogg, 2016). Within this understanding, postulated by the Social Identity Theory, crossover takes place after the social identification with a group, where individuals tend to reach uniformity within that group. Due to the feeling of affiliation a crossover of negative experiences and emotional states, triggered by a specific behavior, can be assumed.

In contrast to the explained negative spillover and crossover of stress factors, also positive spillover and crossover of motivational factors or job resources are assumed in the Spillover-Crossover Model. Figure 2 displays this positive spillover and crossover. Job resources, which lead, according to the Job Demands-Resources Model, to engagement are assumed to spill over from the work-domain to the home-domain and then cross over to a partner (Bakker and Demerouti, 2013). A positive spillover leads to a work-family enrichment (Bakker and Demerouti, 2013).[46] A work-family enrichment arises if the participation in the work-role makes it easier to participate in the family-role, for example due to the virtue of experiences or certain skills (Frone, 2003).[47]

This positive spillover, leading to a work-family enrichment, is followed by a positive crossover to the partner (Bakker and Demerouti, 2013). The positive crossover can be direct or indirect like the negative crossover, too. The direct positive crossover is again characterized by a crossover of the well-being status between partners. Positive experiences in the work-domain spill over to the home-domain and positively affect the partner's well-being through the own well-being. The positive direct crossover can thus also be explained by the Theory of Emotional Contagion, because the positive emotional experiences of other individuals are also empathized due to the synchronization of the facial, vocal and postural expressions. The indirect positive crossover however arises because job resources spill over to the home-domain, leading to a work-family enrichment, which in turn leads to a positive impact on the interaction at the home-domain. This positive impact on the interaction between partners appears in social support leading positively to well-being (Bakker and Demerouti, 2013). Like the indirect negative crossover, also the indirect positive crossover can be explained by the Social Identity Theory. Due to the feeling of affiliation within a group, individuals show a specific behavior which may lead to a crossover of positive experiences and emotional states.

The Spillover-Crossover Model or parts of it have frequently been empiri-

[46] Work-family enrichment is also called work-family facilitation (Frone, 2003).

[47] Like the work-family conflict, also the work-family enrichment can be bidirectional, called family-work enrichment. Family-work enrichment arises if the participation in the family-role makes it easier to participate in the work-role (Frone, 2003).

cally confirmed. Positive spillover and crossover for example are examined by Rodríguez-Muñoz et al. (2014). They find evidence for a positive effect of work engagement on own happiness as well as on partner's happiness on a daily level among Spanish dual-earner couples (Rodríguez-Muñoz et al., 2014). Demerouti (2012) examines positive spillover and crossover of job resources on energy for dual-earner couples in the Netherlands. The results support the Spillover-Crossover Model, because significant effects of job resources on own and on partner's level of energy can be found (Demerouti, 2012). Another example for a study examining positive spillover and crossover comes from Sanz-Vergel and Rodríguez-Muñoz (2013). They investigate if positive experiences at work spill over to the home-domain and affect well-being and in turn, affect partner's well-being by crossover (Sanz-Vergel and Rodríguez-Muñoz, 2013). For a Spanish sample of dual-earner couples significant spillover as well as significant crossover of positive experiences at work can be found (Sanz-Vergel and Rodríguez-Muñoz, 2013).

In contrast to positive spillover and crossover, negative spillover and crossover have been investigated more often (Bakker and Demerouti, 2013). A study by Bakker et al. (2012) for example examines negative spillover and crossover for teachers in Greece. They find out that teachers who lose their work engagement also invest less in the relationship with their partners at home, which in turn leads to depression symptoms observable by the partner of the corresponding teacher. In line with this, Sanz-Vergel et al. (2012) find a negative relationship between emotional labor and own well-being as well as emotional labor and partner's well-being in a diary study among Spanish dual-earner couples. Shimazu et al. (2011) examine the effect of workaholism on individual's and partner's psychological distress for dual-earner couples. They use a large cohort study of Tokyo, called the Tokyo Work-Family INterface Study (TWIN), to examine these negative spillover and crossover of workaholism. Results show significant spillover effects of workaholism on own psychological distress, crossover can however not be confirmed (Shimazu et al., 2011). Another example for a study examining negative spillover and crossover comes from Totenhagen et al. (2017), who, amongst others, examine the effects of external stress on the relationship quality in same-sex couples in the USA. Their results show that the Spillover-Crossover Model also applies for same-sex couples because significant negative effects of external stress on own and partner's expectation about relationship quality could be found (Totenhagen et al., 2017).

Positive and negative spillover and crossover together and hence the Spillover-Crossover Model in a holistic way are examined for example by Bakker et al.

(2013). They use data of the cohort study TWIN to investigate whether work engagement and workaholism have an impact on one's own and partner's family satisfaction. Results of their study present evidence for the Spillover-Crossover Model as they find a positive relationship between work engagement and work-family facilitation, leading to own and partner's family satisfaction and a positive relationship between workaholism and work-family conflict which in turn has a negative effect on own and partner's family satisfaction (Bakker et al., 2013).

The presentation of the Spillover-Crossover Model as well as the variety of empirical studies in consideration of the Spillover-Crossover Model shows, that the Spillover-Crossover Model explains spillover and crossover effects of diverse causes. Hence, when examining experiences at the workplace, the Spillover-Crossover Model should be taken into account.

3.2 The Social Role Theory

The Social Role Theory was developed in the late 1970's by Alice H. Eagly and evolved in the following decades in cooperation with Wendy Wood. The Social Role Theory is based on the general understanding of role theory which states that each individual holds different roles which are associated with requirements about how individuals should behave (Biddle, 1986). A recent version of the Social Role Theory is represented by Eagly and Wood in 2012. The Social Role Theory was developed to explain differences and similarities in individual behavior between women and men (Eagly and Steffen, 1984; Eagly and Wood, 1991, 2011). A sexual division of labor and gender hierarchy is assumed as the root cause of such differences or similarities (Eagly and Steffen, 1984; Eagly and Wood, 1991; Eagly et al., 2000). The Social Role Theory applies for nations, in which women spend more hours in domestic work and fewer hours in paid employment than men do. Nations in which women earn less are concentrated in different occupations or at lower levels of organizational hierarchies or even both. Accordingly, the Social Role Theory applies to nations in which sexual division of labor and gender hierarchy are prevailing (Eagly and Steffen, 1984; Eagly and Wood, 1991; Eagly et al., 2000).

Following the Social Role Theory, the division of labor between women and men is on the one hand due to physical specialization which means that there are certain activities which physically are better suited to women and certain activities which physically are better suited to men. This in turn is reflected in the occupations, women and men work in and the time they spend in such occupations (Eagly and Wood, 2011). On the other hand, the division of

labor between women and men is assumed to be due to local economy, social structure or ecology (Eagly and Wood, 2011).

Figure 3 shows the relationship between the division of labor and the differences in behavior of women and men. It is displayed, that the division of labor leads to gender role beliefs. These gender role beliefs arise, because individuals within a society observe female and male behavior and conclude that differences and similarities go back to corresponding dispositions of the sexes (Eagly and Steffen, 1984; Eagly and Wood, 1991; Eagly et al., 2000; Eagly and Wood, 2011). More detailed, individuals within a society observe the behavior of women and men in their social role and infer that the attributes which are required by their social roles, are attributes going back to dispositions of the sexes and not going back to role requirements. Women and men are assumed to hold attributes which are suited to the roles they typically take within a certain society (Eagly and Wood, 1991). Such attributes become stereotypic for women and men and gender-role beliefs arise (Eagly and Wood, 2011). Therefore, gender roles are defined as socially shared behavioral expectations which are directed to individuals based on their sex (Eagly et al., 2000). Gender stereotypes are defined as socially shared beliefs about individual attributes of women and men (Ashmore and Del Boca, 1979; Eagly and Steffen, 1984).

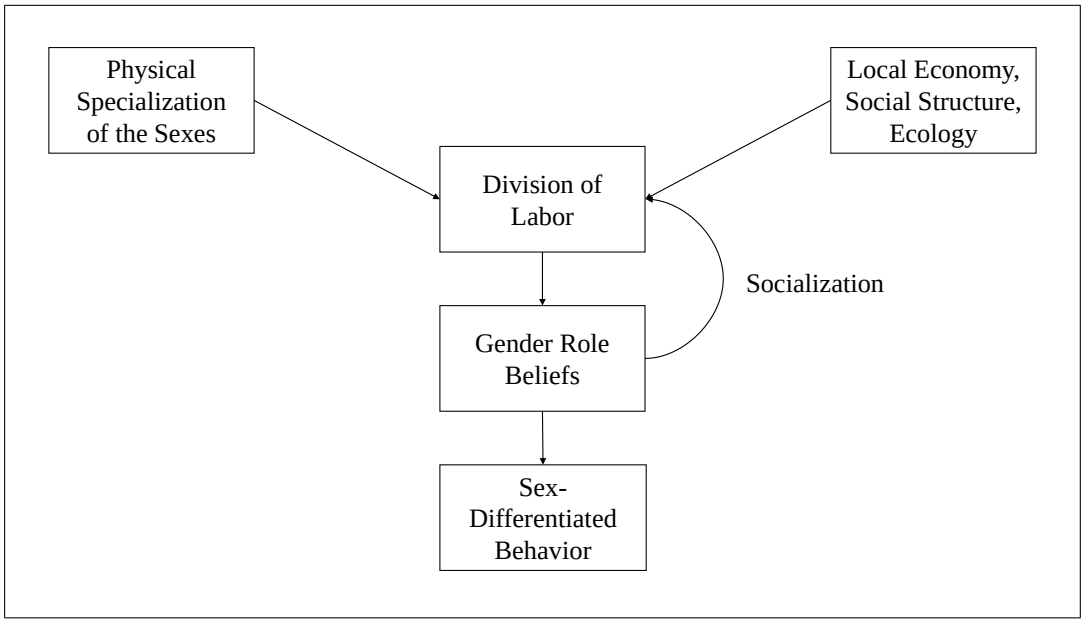

Figure 3: Social Role Theory
(Source: Own presentation according to Eagly and Wood (1991).)

Based on gender stereotypes, men are assumed to be strong on achievement traits, forceful, independent, masterful, assertive, decisive and ambitious (Eagly and Wood, 1991; Heilman, 1995). Women however, are assumed to be strong

on nurturer and affiliation traits as well as tender, understanding, friendly, unselfish, emotionally expressive and being concerned with others (Eagly and Wood, 1991; Heilman, 1995).[48] Following the Social Role Theory, stereotypic attributes as well as the shared gender role beliefs are consolidated in the process of socialization. The society promotes personality traits and skills differently for girls and boys to prepare them for their usual family and work roles (Eagly and Wood, 2011). Such a process of socialization leads women to have a stronger identification with the family role than with the work role and men to have a stronger identification with the work role than with the family role. This in turn again facilitates the division of labor between women and men (Simon, 1992; Barnett et al., 1995; Eagly and Wood, 2011).

As displayed in Figure 3, gender role beliefs result in sex-differentiated behavior. Considering the Social Role Theory, this happens through three different mechanisms. The first mechanism is the hormonal regulation, the second mechanism the self-regulation and the third mechanism is the social regulation (Eagly and Wood, 2011). The influence on the behavior of women and men through hormonal processes means the assistance of culturally masculine and feminine behavior due to hormones (Eagly and Wood, 2011). For example, testosterone in men supporting dominance behavior for assertiveness as stereotype for men.

Gender role beliefs lead to a certain behavior due to self-regulation while women and men adopt their behavior to standards set by themselves. Following the Social Role Theory, these women's and men's own standards arise because the self-concepts of women and men are influenced by gender roles, which in turn leads to gender identities (Eagly and Wood, 2011). Women and men accept or even support the expectations which are associated with their sexes and incorporate gender roles into their self-concept. The degree of incooperation differs according to the individuals (Eagly and Wood, 2011). An accordance of the current behavior of an individual and its self-standards leads to positive emotions and an increase of self-esteem. A deviation of the current behavior from the self-standards however, leads to negative emotions and decreases self-esteem. Therefore, self-regulation occurs and adopts the current

[48] Only a selection of attributes is presented here. More gender specific attributes can be found in Bem (1974). The following attributes can be derived from his developed Sex Role Inventory: Women are affectionate, cheerful, childlike, compassionate, do not use harsh language, eager to soothe hurt feelings, flatterable, gentle, gullible, love children, loyal, sensitive to the needs of others, shy, soft-spoken, sympathetic, tender, understanding, warm, and yielding. Men act as leaders, are aggressive, ambitious, analytical, assertive, athletic, competitive, defend own beliefs, dominant, forceful, have leadership abilities, independent, individualistic, make decisions easily, self-reliant, self-sufficient, have a strong personality, willing to take a stand, and willing to take risks.

behavior of individuals to their self-standards (Eagly and Wood, 2011).

The third mechanism is the social regulation. According to the Social Role Theory, women and men adjust their behavior as a result of shared expectations within a society. This adoption occurs, because individuals are rewarded by the other individuals within the society, if they correspond with their gender role and are punished if they do not (Eagly and Wood, 2011). Punishment is shown with refusal of social interaction, for example being dismissed or ignored. Hence, behavior which is not conform with the respective gender role, causes costs and these costs will only be accepted if benefits exceed the costs (Eagly and Wood, 2011).

The Social Role Theory or parts of it have been confirmed in several empirical studies.[49] One of the recent studies has been conducted by Haines et al. in 2016. They examine if gender stereotypes still exist and whether they changed over time since the participation of women in the labor market has raised. Considering the Social Role Theory, gender roles and gender stereotypes change, if the social role structure changes, as it is assumed that gender role beliefs are rooted in the division of labor (Eagly et al., 2000). Following this assumption, the raising participation of women in the labor market should lead to changing gender role beliefs and in turn to more behavioral flexibility (Eagly et al., 2000). This could however not be confirmed by Haines et al. (2016). Their study shows that gender stereotypes still exist and represent the basic social beliefs about the sexes (Haines et al., 2016). These findings are not necessarily contrary to the assumptions of the Social Role Theory, but represent that a change of gender stereotypes has not yet occurred, but does not preclude this from happening. This is in line with Eagly et al. (2000), expecting that gender roles are in flux but not clearly changed until now.

Comprehensively, gender role beliefs as well as gender stereotypes are still existing (Haines et al., 2016). These gender role beliefs and gender stereotypes in turn still affect the process of socialization of girls and boys, which leads women to have a stronger identification with the family role and men to have a stronger identification with the work role (Simon, 1992; Barnett et al., 1995; Eagly and Wood, 2011). Hence, when examining work and family roles the varying identification of women and men with these roles should be taken into consideration, even though it has been found that experiences in strong identified roles are more important than experiences in less identified roles (Kessler and McLeod, 1984; Wheaton, 1990; Simon, 1992; Thoits, 1992).

[49] An overview of empirical studies can be found in Eagly and Wood (1991). Fore more recent empirical studies see e.g. Koenig and Eagly (2014), Steinmetz et al. (2014), Miller et al. (2015) or Zhao et al. (2015).

4 Hypotheses

Considering the Spillover-Crossover Model and especially the fist part of the Spillover-Crossover Model, job demands are assumed to cause strain which spill over from the work-domain to the home-domain and lead to a work-family conflict. Those work-family conflicts in turn affect the well-being of an individual who suffers from job demands (Bakker and Demerouti, 2013). Job demands are defined as job characteristics that call for physical or mental effort and cause physiological and psychological costs (Bakker and Demerouti, 2013). Regarding job demands, the empirical evidence of the Spillover-Crossover Model demonstrates that such strain or negative experiences at work can arise through diverse causes. For example workaholism (Shimazu et al., 2011; Bakker et al., 2013), work overload (Shimazu et al., 2009) or lost work engagement (Bakker and Demerouti, 2013) are found to lead to a work-family conflict and in turn to a spillover to the individual's well-being. In general, the Spillover-Crossover Model assumes that all job demands can cause strain and trigger spillover to well-being trough a work-family conflict (Bakker and Demerouti, 2013).

Job resources are assumed to produce engagement, which in turn is assumed to cause a positive spillover from the work-domain to the home-domain and leads to work-family enrichment. Job resources are defined as physical, psychological, social or organizational aspects supporting to achieve work goals, reducing costs which arise because of job demands and stimulating personal development and growth (Demerouti et al., 2001). Previous literature for example identifies work enjoyment (Sanz-Vergel and Rodríguez-Muñoz, 2013) or work engagement (Bakker and Xanthopoulou, 2009; Culbertson et al., 2012; Clark et al., 2014) as leading to positive spillover.

In the sense of these definitions of job demands and job resources, job insecurity can be classified as a job demand and not as a job resource (Schaufeli and Taris, 2014). Several empirical studies have identified job insecurity as a work stressor (e.g. Ashford et al. (1989); Barling and Kelloway (1996); Fox and Chancey (1998); Mauno et al. (2001); Gilboa et al. (2008); Goh et al. (2016)), while a work stressor is defined as a stressful job condition by Jex et al. (2003). In this sense, job stress means the uncomfortable and undesired awareness or feeling of an employee, who is required to depart from his normal or self-desired functioning in his job, which may result in dysfunctional psychological or physiological consequences (Parker and DeCotiis, 1983). Therefore, job insecurity identified as work stressor can clearly be classified as a job demand (Demerouti et al., 2001; Kinnunen et al., 2010; Bakker and Demerouti, 2013;

Schaufeli and Taris, 2014).

Physiological and psychological costs are considered as consequences of job demands, showing a comprehensive understanding of well-being including physical as well as mental aspects (Bakker and Demerouti, 2013). A decrease in the mental health status of an individual is thereby to be assigned to psychological cost and can hence be classified as a consequence of job demands in terms of the Spillover-Crossover Model.

In summary, regarding the first part of the Spillover-Crossover Model and concentrating on negative spillover of job demands, it is assumed, that job insecurity as a job demand causes strain, which spills over from the work-domain to the home-domain and leads to a work-family conflict. The work-family conflict in turn negatively affects the mental health status of an individual. This assumption is supported by empirical evidence for a relationship between job insecurity and mental health. For example, Reichert and Tauchmann (2017) examine the association between job insecurity and mental health indirectly, while investigating individuals in firms with workforce reduction between 2002 and 2010 for Germany. They find a strong negative effect between workforce reduction and the mental health status as well as a mediating effect of subjective job insecurity on the relationship between workforce reduction and the mental health status. For Germany, the relationship between job insecurity and the mental health status is furthermore identified between 1999 and 2009 by Bethge et al. (2008) and Otterbach and Sousa-Poza (2016). Fiori et al. (2016) find significant evidence for the association between experienced job insecurity and mental health for young adults in Italy. Also for the USA and for Switzerland a significant relationship between job insecurity and mental health could be proven. Lam et al. (2014) examine subjective job insecurity and mental health against the background of changing economic climate in the USA. Debus and Unger (2017) however examine the indirect relationship between subjectively measured job insecurity and the mental health status by work engagement in Switzerland. Näswall et al. (2005a) find a negative relation between subjective job insecurity and mental health, while using data of a Swedish retail organization in restructuring.[50] This leads in summary to the following hypotheses, which are differentiated by female and male individuals like in the Spillover-Crossover Model:

[50] An overview of studies examining the relationship between job insecurity and mental health can be found in e.g. Kim and von dem Knesebeck (2015) or De Witte et al. (2016).

H1a: *If a woman suffers from job insecurity, the mental health status of this woman is worse than the mental health status of a woman, who does not suffer from job insecurity.*

H1b: *If a man suffers from job insecurity, the mental health status of this man is worse than the mental health status of a man, who does not suffer from job insecurity.*

The next hypothesis is based on $H1a$ and $H1b$ and hence on the Spillover-Crossover Model, but additionally considers differences across gender. Following the Social Role Theory represented in Chapter 3.2, the division of labor between women and men leads to gender role belief which in turn affects the process of socialization of girls and boys. Such process of socialization then leads women to have a stronger identification with the family role and men to have a stronger identification with the work role (Eagly and Wood, 2011). A wide range of research about the labor division in Germany shows, that this process is indeed still present today. For example, Bredtmann (2014), Ancharski (2015), Camp et al. (2016) or Wimmer (2016) examine the participation and role allocation of women and men in Germany and especially at the German labor market and display results which are in line with the process, assumed by the Social Role Theory.

The different identification of women and men with the work-role and the family-role is in turn assumed to lead to a different vulnerability to role strain for women and men. Such a different vulnerability may lead to a stronger impact of work strain on the mental health status of men than of women, because of men's stronger identification with the work role. Empirical evidence regarding such a different vulnerability to role strain for women and men has already been identified in earlier research. Simon (1992) confirms that strain in strong identified roles is more threatening to well-being than strain in less identified roles. In line with this, several studies have found that changes in experiences at work are more important for men than for women and changes in material experiences however are more important for women than for men (e.g. Kessler and McLeod (1984); Wheaton (1990); Simon (1992); Thoits (1992)). These results therefore are in line with the Social Role Theory. In summary, considering the different vulnerability to role strain for women and men, differences in the spillover of job insecurity on the mental health status across gender are assumed, leading to the following hypothesis:

H1c: *If a man suffers from job insecurity, his mental health status is worse than the mental health status of a woman, who suffers from job insecurity.*

Next to the spillover effects of strain from the work-domain to the home-domain, crossover effects are also considered in the Spillover-Crossover Model (Bakker and Demerouti, 2013). Crossover and hence the transmission of experiences in the home-domain across individuals, is assumed to arise after spillover has occurred. Thereby, job demands experienced by an individual are identified to cause negative crossover affecting the individuals' partner (Bakker and Demerouti, 2013). Therefore, it is assumed, that job insecurity as a job demand does not only cause strain which spills over to the home-domain, but also affects the partner's mental health status by crossover. Considering the Spillover-Crossover Model, not only one's own job insecurity but also partner's job insecurity is assumed to affect the individuals' mental health status. Thereby, crossover between partners from male individuals to female individuals as well as from female individuals to male individuals are conceivable following the Spillover-Crossover Model. Hence, this leads to the following hypothesis about crossover of job insecurity to the mental health status for women and men:

H2a: *If a woman is in a relationship with a partner, who suffers from job insecurity, the mental health status of this woman is worse than the mental health status of a woman being in a relationship with a partner, who does not suffer from job insecurity.*

H2b: *If a man is in a relationship with a partner, who suffers from job insecurity, the mental health status of this man is worse than the mental health status of a man being in a relationship with a partner, who does not suffer from job insecurity.*

Crossover in general can either be direct or indirect (Bakker and Demerouti, 2013). Within the Spillover-Crossover Model, a crossover of strain to a partner, through the well-being status of the other partner, is considered as a direct crossover (Bakker and Demerouti, 2013). Such a direct crossover is based on the Theory of Emotional Contagion (Hatfield et al., 1993) and therefore assumed to occur due to an empathic reaction of the partner, which triggers an increase in the strain level of this partner (Bakker and Xanthopoulou, 2009). A worse mental health status of an individual's partner can hence be traced back to a worse mental health status of an individual. An indirect crossover however, is assumed in the Spillover-Crossover Model to occur due to a negative interaction at the home-domain, which then affects the partner's well-being (Bakker and Demerouti, 2013). Regarding a worse mental health status of an individual, a negative interaction between this individual and the individual's

partner at the home-domain affects the mental health status of the individual's partner. Thereby, the indirect negative crossover can be explained by the Social Identity Theory (Tajfel and Turner, 1979). Under consideration of the Social Identity Theory, individuals within a certain group tend to reach uniformity within this group due to the feeling of affiliation (Tajfel and Turner, 1979). This aim for uniformity may trigger the crossover of negative experiences and emotional states within a certain group. Within a couple, which represents a group of two members, a worse mental health status of an individual leads to a specific behavior of this individual regarding the interaction with the other group member, the partner. This in turn may lead to a worse mental health status of the partner as well.

Taking the Social Role Theory in consideration, the stronger identification of women with the family role than with the work role and the stronger identification of men with the work role than with the family role, lead to the assumption that it is more sustainable, if men deviate from their work role than if women do (Simon, 1992). Regarding the crossover of strain, this stronger vulnerability of men in turn is assumed to be also expressed in crossover. The stronger impact of work-role strain for men leads to a worse mental-health status for men than for women. This worse mental health status of men in turn affects the mental health status of women due to empathic reaction, when direct crossover is considered, by a higher degree than the less affected mental health status of women would do. Regarding indirect crossover, the worse mental health status of men leads to a more negative impact on the interaction at the home-domain than the less affected mental health status of women would do. Comprehensibly, men's work role strain is assumed to have a stronger impact than women's work role strain due to the different vulnerability of work strain for women and men. Applying the relationship between job insecurity and the mental health status of an individuals' partner, men's job insecurity is assumed to have a stronger effect considering crossover and hence a stronger effect on women's mental health status than women's job insecurity on men's mental health status. Therefore, the following hypothesis is formulated:

H2c: *If a woman is in a relationship with a man who suffers from job insecurity, the mental health status of this woman is worse than the mental health status of a man, who is in a relationship with a woman who suffers from job insecurity.*

All together, the hypotheses structure to answer the research question regarding spillover and crossover of job insecurity to the mental health status as

well as those considering the different vulnerability of spillover and crossover for women and men are displayed in Figure 4. The upper part of the figure represents the spillover hypothesis $H1a$ for women (Wm) and hence the relationship between the women's job insecurity and the women's mental health status. The lower part of the figure however displays spillover hypothesis $H1b$ for men (M) and hence, men's job insecurity in relation to men's mental health status. The hypotheses $H2a$ and $H2b$ are displayed between the individuals. The relation between men's job insecurity and women's mental health status is displayed ($H2a$) as well as the relation between women's job insecurity and men's mental health status ($H2b$). The hypotheses $H1c$ and $H2c$ regarding the different vulnerability for women and men arise by the comparison of spillover and crossover of job insecurity to the mental health status.

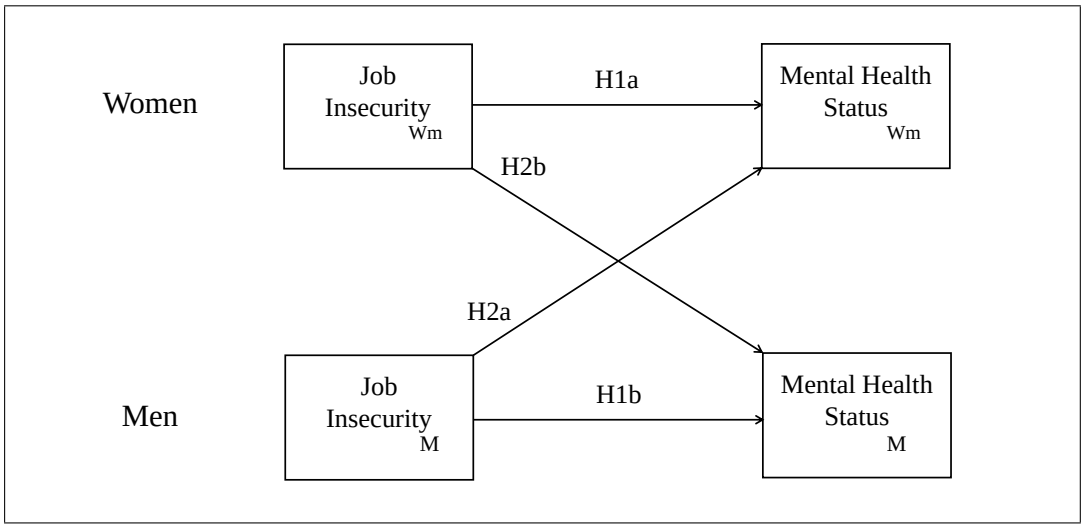

Figure 4: Research Hypotheses
(Source: Own presentation.)

5 Data

5.1 German Socio-Economic Panel and Sample

To examine the established hypotheses and analyze spillover and crossover of job insecurity to the mental health status within a couple, it is necessary to use a dataset consisting of information on both partners within a couple. A dataset which provides such information is the GSOEP. The GSOEP is a longitudinal representative panel dataset of private households in Germany, which has been started in 1984. The private households are re-interviewed annually and thereby approximately 11,000 households and 20,000 individuals are questioned. The GSOEP consists of objective information on individuals like age, gender, education or the working history as well as subjective information like self-reported mental and physical health status or satisfaction with work or family life.[51] Using the GSOEP, it is possible to link information of partners by collecting information about person- and household-numbers of the observed individuals. This allows to generate a dataset which contains observations of the same variables for the individual himself and for the partner of the individual in a given year.[52]

For the following analysis, it is focused on a sample of heterosexual dual-earner couples living together in one household. Thereby, dual-earner couples and hence couples with two employed partners are selected, because job insecurity can only occur considering employed individuals and is therefore exclusively collected for employed individuals in the GSOEP. For the same reason, age is limited up to 65 years, because it represents the German retirement age for the individuals in the sample.[53] Furthermore, due to the assumed differences across gender concerning spillover and crossover effects, the sample has to be restricted to heterosexual couples and hence to couples each existing of a male and a female partner. Gender differences could however not be investigated in homosexual couples. It is additionally concentrated on couples living together in one household to ensure that the opportunity of a crossover exists overall. For such couples, it is assumed that interactions within the home-domain take

[51] For more information see http://www.diw.de. As well as Haisken-DeNew and Frick (2005), Wagner et al. (2007), Wagner et al. (2008) and Schupp (2009).

[52] Version v30 of the GSOEP (DOI: 10.5684/soep.v30) is used which was the most recent available wave of the GSOEP when starting the analysis of this dissertation. The data was extracted using the Add-On package PanelWhiz for Stata. PanelWhiz was written by Dr. John P. Haisken-DeNew. For more information see Haisken-DeNew and Hahn (2010).

[53] The increase in the retirement age in Germany does not apply to the selected sample, since 2012 is the last observed year and individuals over 65 have on average already been retired.

place and hence the possibility of crossover is given. Couples not living together in one household however do not share the same home-domain, which may prevent crossover. It is furthermore not possible to control for daily or even weekly interaction between the members of couples living separately and hence, they are not included into the used sample to avoid bias. Finally, the sample is restricted to the years 2002, 2004, 2006, 2008, 2010 and 2012. This limitation concerning the observed years is due to the availability of the health-variable in the dataset. After all restrictions, the sample exists of 31,316 individual-year observations, whereas not all individuals are observed in each year.

5.2 Variables and Measuring Methods

The dependent variable, the mental health status of an individual, is measured in the GSOEP since 2002 for every second year with the MCS based on the SF-12v2 (Andersen et al., 2007). Hence, the MCS is measured in the years 2002, 2004, 2006, 2008, 2010, 2012. The MCS is thereby elaborated with six questions starting with the expression „During the last four weeks, how often did you:“ followed by different questions about certain feelings. Thereby, the number of questions for the different dimensions of the mental health status in the GSOEP are in line with the original SF-12v2, but questions in the GSOEP deviate to some degree from the original SF-12v2 in the formulation, the order and the layout (Andersen et al., 2007).[54] The response options for each of the questions are „always“, „often“, „sometimes“, „almost never“ and „never“(Andersen et al., 2007).[55]

The scoring of the MCS in the GSOEP is carried out by the following steps. First, the four subscales of the MCS, vitality, social functioning, role-emotional and mental well-being are created. Therefore, the mean of each subscale is calculated. For the subscales role-emotional and mental well-being, which consist of two items each, the arithmetical means are calculated. After this, the subscales are transformed to a scale ranging from 0 to 100 (Nübling et al., 2006; Andersen et al., 2007). In a next step, the four scales are z-standardized (mean = 0, standard deviation = 1) using the means and standard deviations from the GSOEP wave of the year 2004 consisting of 21,248 observed individuals (Nübling et al., 2006; Andersen et al., 2007). The z-score standardization is thereby run through subtracting the mean from each subscale score and dividing the difference by the corresponding standard deviation from the GSOEP-

[54] A comparison of the questions of the original SF-12v2 MCS and the GSOEP version of the SF-12v2 MCS can be found in the Appendix in Table 28.

[55] In the German version the response options are called: „Immer“, „Oft“, „Manchmal“, „Fast nie“ and „Nie“.

data of 2004. A mean of 50 and a standard deviation of 10 is then established through linear transformation to achieve a better handling (Nübling et al., 2006; Andersen et al., 2007).

Furthermore, an EFA is carried out to set up the component summary scale MCS out of the four subscales. Thereby, the rotated factor loadings displayed a clear assignment of the four subscales vitality, social functioning, role-emotional and mental well-being to the superordinate scale, the MCS (Nübling et al., 2006; Andersen et al., 2007). The factor score coefficients are then used to weight the four subscales, which in addition are summed up to a component score, the MCS (Nübling et al., 2006; Andersen et al., 2007). Again, using linear transformation, the mean and the standard deviation of the MCS is set to 50 respectively 10 (Nübling et al., 2006; Andersen et al., 2007). The MCS is provided in the GSOEP, so that no own scoring has to be undertaken by the users of the GSOEP. Hence, the provided MCS within the GSOEP is used for the following analysis.

The independent variable job insecurity is measured in the GSOEP by a question which is divided into two parts. The upstream question, „How concerned are you about the following issues?“, is followed by the expression „Your job security“. Thereby, the response options are: „very concerned“, „somewhat concerned“ and „not concerned at all“.[56] In the GSOEP, it is additionally asked for the probability of loosing a job with the response options 0% to 100%. Considering the definition of job insecurity, established in Chapter 2.1.1, as the subjective concern about the permanence of a job, it is obvious that the question asking for concerns about job security applies much better than the question asking for the job loss probability. Furthermore, for job loss probability it is only asked every two years and not in the same years in which the dependent variable, the mental health status, is measured. Hence, only a time-displaced analysis would be possible using the question asking for job loss probability.[57] Summarized, to measure job insecurity, the question regarding concerns about job security is used. This question is asked since the first waves of the GSOEP in 1984 and is collected every year.

For the following analysis, the variable job insecurity will be recoded to a binary variable measuring job insecurity with the response options 0 and 1 corresponding to „no“ and „yes“. The response options „very concerned“ and „somewhat concerned“ together represent *job insecurity*, whereas the response

[56] In the German version this question is called: „Wie ist es mit den folgenden Gebieten - machen Sie sich da Sorgen? - Um die Sicherheit Ihres Arbeitsplatzes?“ with the response options: „Große Sorgen“, „Einige Sorgen“ und „Keine Sorgen“.

[57] The probability of losing a job is asked in 1999, 2001, 2003, 2005, 2007, 2009 and 2013.

option „not concerned at all“ displays *job security*. This approach is in line with earlier research of job insecurity (e.g. Clark et al. (2010), Reichert and Tauchmann (2011), Reichert et al. (2015) or Otterbach and Sousa-Poza (2016)) and enables a more adequate interpretation of the effects of job insecurity than a continuous operationalisation would do. Furthermore, it is useful with the background of the established hypotheses (see Chapter 4), as it is not seeked to examine different levels of job insecurity along the continuum of job insecurity, but the existence of job insecurity or job security itself. Next to own job insecurity, also job insecurity of the partner will be included as an independent variable. The variable measuring if the partner suffers from job insecurity is represented by a dummy variable with the response options 1 for „yes“ and 0 for „no“, corresponding to the variable measuring own job insecurity. The other relevant independent variable is represented by gender which has been asked in the GSOEP since 1984 for each year. Thereby, the gender of an individual has a particular role for the following analysis, as it is essential to verify the hypotheses including gender differences. Gender is measured using a dummy variable, which takes the value 1 for male individuals and 0 for female individuals.

Also included in the analysis are a couple of control variables. These variables are identified using a meta-analysis by Kim et al. (2012). Their analysis includes studies which deal with job insecurity and health, and are published between 1988 and 2010. The studies are detected by searching in the databases PubMed, PsychINFO, Stork Social Science Citation Index and Index Lilac (Kim et al., 2012).[58] Additionally, an own literature research was performed to include also economic databases and to broaden the period of time until today. Furthermore, health was specified to mental health. It was searched for articles between 1988 and 2017 in the economic databases Business Source Premier, EconLit and Econbiz as well as in the databases PsycINFO, PubMed and Scopus to include the field of psychology, health and social science, as well.[59] All control variables are selected, which are found to have a significant influence in more than three of the studies and are available in the GSOEP. This is done in order to obtain a manageable number of control variables, which are frequently used in research and are accessable for the following analysis. Thereby, age, occupation and education could be identified as important

[58] For more information on the selection of studies, see Kim et al. (2012).

[59] In all databases it was searched for the keywords „Job Insecurity“ and „Mental Health“. The results were restricted to be written in English and peer reviewed. Duplicate articles were excluded. Version of September 2017.

control variables.[60]

The age of an individual is represented by a continuous variable, measuring the current age of the corresponding individual. It is raised in each wave of the GSOEP since the first waves in 1984. Once age is included into the analysis models, it is grand-mean centered to enable a better interpretation of the results as age otherwise does not contain a natural zero (Krause and Urban, 2013).

The educational background of an individual is measured with a continuous variable, representing the years an individual has spent in education. The number of years of education consists of the years of schooling and the years of occupational training. Thereby, for the years of schooling the following classification is given; less than 7 years means no degree, 9 years a lower school degree, 10 years intermediary school or others, 12 years a degree for a professional college and 13 years a high school degree (Schupp et al., 2014).[61] The additional years of occupational training are added as follows; 1.5 years for an apprenticeship, 2 years for technical schools (incl. health), 1.5 years for civil servants apprenticeship, 3 years for higher technical college and 5 years for university degree (Schupp et al., 2014).[62] When education is included into the analysis models as control variable, it is grand-mean centered like the variable measuring age. This is done in order to enable a useful interpretation of the results because the variable otherwise does not have a natural zero (Krause and Urban, 2013).

The variable controlling for the occupation of an individual in the GSOEP, is based on the International Standard Classification of Occupations (ISCO). Considering the ISCO, occupations are organized hierarchical by considering complexity, whereas the lowest level represents jobs which can be executed by one person (ILO, 2004b). The occupations in the ISCO are divided into 10 major groups and diverse sub-major groups, minor groups and unit groups. Thereby, the grouping is done by similarity in tasks and duties of the different jobs (ILO, 2004b).[63] For the following analysis, the occupations are summarized to the 10 major groups (0-9). Group 0 thereby includes armed forces. The first group includes legislators, senior officials and managers. Professionals represent the second group. The third group comprises technicians and

[60] The use of this control variables are in line with previous studies, using the GSOEP. See e.g. Bethge et al. (2008).

[61] For a high school degree, 13 years in education are considered regardless of achieving the degree in G8 or G9 (Schupp et al., 2014).

[62] The Bachelor/Master system of German universities is not yet noticed in the calculation of the years in education in the GSOEP (Schupp et al., 2014).

[63] For more information regarding the ISCO, see ILO (2004b).

associate professionals. Clerks represent the fourth group. Group five consists of service workers, shop sales workers and market sales workers. Skilled agricultural and fishery workers represent the sixth group. Craft workers and related trade workers however represent the seventh group. Plant operators, machine operators and assemblers are summarized to group eight and group nine is represented by elementary occupations (ILO, 2016).[64]

For the following analysis, each major group is represented by a dummy variable to enable a meaningful interpretation of the different occupation effects. The dummy variables measure the affiliation of an individual to one of the major groups. Hence, affiliation is coded with 1 and no affiliation with 0. The ninth group is thereby used as base category and hence not included into the model. Furthermore, because the sixth group, skilled agricultural and fishery workers are underrepresented in the used sample, group six and group seven are merged.[65] Group 0 is however completely erased from the analysis to avoid bias, which arises because of outliers as the group is hardly represented.[66]

[64] Meanwhile the ISCO has been revised and the ISCO-08 has been introduced in 2008. However, at the time of this dissertation the ISCO-08 is only available for 2013 (using version v30 of the GSOEP) and can hence not be applied for the analysis. For more information of the ISCO-08, see ILO (2004a).

[65] The sample only consists of 268 skilled agricultural and fishery workers.

[66] Only 67 individuals in the sample are working as armed forces. These individuals are therefore excluded.

6 Methodology

6.1 The General Concept of Multilevel Modeling

MLM or often also called Hierarchical Linear Modeling or Mixed Modeling is used when the assumption of independence of the Multiple Regression Analysis is violated and hence, when non-independent data should be analyzed (Raudenbush and Bryk, 2002; Hosoya et al., 2014). Thereby, non-independent data usually arises when observations have a hierarchical, a clustered or a grouped structure. Such data is called „nested data“ (Hosoya et al., 2014; Hoffman, 2015). In literature a typical example for nested data are children in classrooms (Raudenbush and Bryk, 2002; Rabe-Hesketh and Skrondal, 2012; Hosoya et al., 2014; Hoffman, 2015). In economic sciences an example can be given by employees within companies or individuals within regions within countries. Furthermore, MLM is used when observations are nested within individuals, because individuals are observed at different points in time (Rabe-Hesketh and Skrondal, 2012; Hoffman, 2015). Analyzing nested data with standard statistical procedures and ignoring the nested structure violates the assumption of independence and results in biased variances, which in turn affect the standard errors of test statistics and lead to biased statistical significance. Therefore, it is important to consider nested structures of data in the case of their existance (Rabe-Hesketh and Skrondal, 2012; Hoffman, 2015).

MLM is suitable for this kind of data, because it takes units of observation at different „levels“ into account and therefore considers the nested structure of the data (Raudenbush and Bryk, 2002; Rabe-Hesketh and Skrondal, 2012; Hosoya et al., 2014; Hoffman, 2015). The examples above show that a nested structure can be divided into two, three or even more levels. Usually, when using MLM, the lower level is designated as level-1, and the upper levels correspondingly are referred to as level-2, level-3 and onwards (Raudenbush and Bryk, 2002; Rabe-Hesketh and Skrondal, 2012; Hosoya et al., 2014; Hoffman, 2015). Thereby, units from the lower level, which are within the same upper level unit, tend to be more similar to each other than units from other upper level units, representing the non-independence of nested data (Rabe-Hesketh and Skrondal, 2012; Hoffman, 2015). Figure 5 displays the different levels of nested data of MLM by considering the example of employees who are nested within companies.

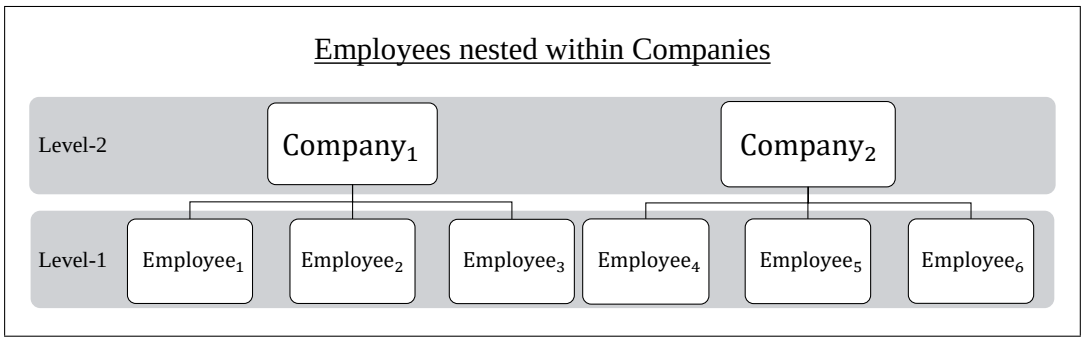

Figure 5: Exemplary Presentation of Nested Data Structure.
(Source: Own presentation.)

Two different companies are exemplarily presented at level-2, the company-level, and six different employees of the different companies are displayed at level-1, the employee-level or individual-level. Employee_1, Employee_2 and Employee_3 are working in Company_1. Employee_4, Employee_5 and Employee_6 are working in Company_2.

In contrast to multiple regression models, multilevel models additionally examine the variation of effects of upper levels (Raudenbush and Bryk, 2002; Rabe-Hesketh and Skrondal, 2012; Hosoya et al., 2014; Hoffman, 2015). This is done by additionally estimating the intercept and/or the slope of a lower level variable as a function of a fixed and a random part at an upper level. Therefore, MLM treats the variance of the intercept and/or the slope at a lower level as random. This approach enables to model the non-independence of longitudinal nested data (Rabe-Hesketh and Skrondal, 2012; Hosoya et al., 2014; Hoffman, 2015). Thereby, multilevel models are usually estimated by Maximum Likelihood Estimation (ML) (Hoffman, 2015).[67]

Using MLM features several advantages. It is possible to estimate the influence of upper level effects on lower level units (Hosoya et al., 2014; Hoffman, 2015). For example, considering again companies at the upper level (level-2) and employees at the lower level (level-1). The effect of a company's location at the company level (level-2) on the job satisfaction of employees at the employee level (level-1) can be examined using MLM. Furthermore, it can be examined whether variables at upper levels moderate the relationship between variables at lower levels (Hosoya et al., 2014; Hoffman, 2015). Regarding once again employees, who are nested within companies, it can be examined if the relationship between working hours and job satisfaction (relationship

[67] For more information on ML see Eliason (1993) or Gould et al. (2006). Other methods are Restricted Maximum Likelihood (RML) or Iterative Generalized Least Squares (IGLS) estimations (Hoffman, 2015). In the following, if it is not expressly mentioned differently, ML estimation is assumed.

at level-1) is moderated by the company's location (variable at level-2). In general, MLM holds the same advantages as multiple regression models, because a multilevel model represents an extent to a multiple regression model. Therefore, for example while estimating multilevel models, it is possible to include categorical variables as well as continuous variables or even both into a multilevel model (Hosoya et al., 2014; Hoffman, 2015). Additional advantages arise when considering specific kinds of nested data. Depending on the nested data which shall be examined, MLM can furthermore be differently developed because MLM comprises a group of multivariate statistical methods. For a detailed compliance of MLM it is useful to consider the specific kinds of data which shall be modeled (Hoffman, 2015). To demonstrate the use of MLM for this specific kinds of data, MLM for longitudinal data and MLM for dyadic data will be presented in the following. After this MLM for a combination of longitudinal and dyadic data, called longitudinal dyadic data, will be deduced by the previously presented information.

6.2 Multilevel Modeling of Longitudinal Data

6.2.1 Peculiarity of Longitudinal Data

Longitudinal data, also called panel data, represents repeated observations on the same subjects. Due to the fact that it contains observations on multiple occasions and multiple units, it is a combination of cross-sectional and time series data (Frees, 2004; Skrondal and Rabe-Hesketh, 2008). Usually, longitudinal data involves information on individuals at different points in time. In the following explanations of longitudinal data the used vocabulary is therefore adapted to this kind of longitudinal data.

The advantage of using longitudinal data is that such data provides information about between-person variation and within-person variation (Hoffman, 2015). Between-person variation represents the inter-individual differences (differences between individuals) which are time-invariant. Within-person variation however shows the intra-individual differences (differences from the individual baseline level) which are time-varying (Hoffman, 2015). Thereby, the relationship between a dependent and an independent variable/independent variables can be considered between-person and/or within-person (Hoffman, 2015).

The dependent variable of a longitudinal analysis is always time-varying, because it always changes over time for some individuals (Rabe-Hesketh and Skrondal, 2012). The independent variables however are time constant or time-

varying. An example for a constant independent variable is origin which does not change over time. An example for a time-varying variable is life satisfaction which can take different values over a life circle. Thereby, the time-varying independent variables can further be differentiated into occasion-specific and occasion- and subject-specific independent variables (Rabe-Hesketh and Skrondal, 2012). Occasion-specific variables change by time and are equal for all individuals, for example year or month. Occasion- and subject-specific independent variables however vary by time and individuals, for example tenure or the number of children. The different kinds of variables in longitudinal data are represented graphically in Figure 6. The left part of Figure 6 displays the possible kind of the dependent variable of longitudinal data and the right part the possible kinds of the independent variables of longitudinal data.

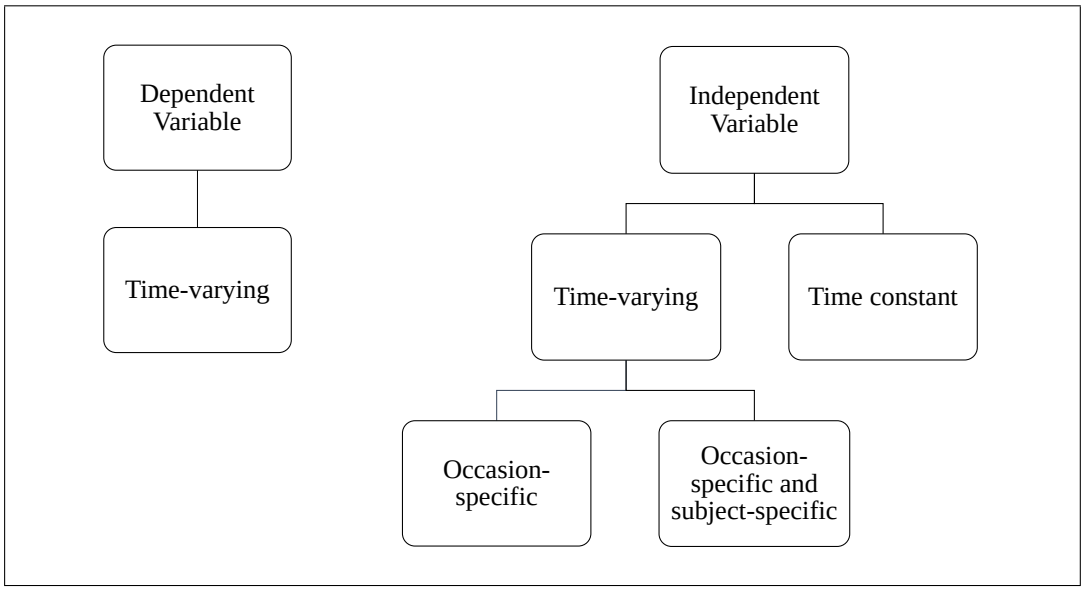

Figure 6: Dependent and Independent Variables of Longitudinal Data.
(Source: Own presentation.)

Longitudinal data can generally be differentiated into balanced and unbalanced occasions (Skrondal and Rabe-Hesketh, 2008). Balanced occasions mean that all individuals are measured at the same points in time without missing observations. Unbalanced occasions however imply that the individuals are observed at different points in time (Skrondal and Rabe-Hesketh, 2008). Not all possible methods that are able to analyze longitudinal data, can deal with unbalanced occasions. Therefore, it is important to determine whether there are balanced or unbalanced occasions before analyzing longitudinal data. Thereby, regardless of being balanced or unbalanced, longitudinal data is characterized by dependency which means that observations of the same individuals will tend to be more similar than observations of different individuals (Hoffman, 2015).

Hence, residuals of the same individuals tend to be correlated. This correlation violates the assumption of independent residuals in standard analysis methods, leading to biased variances, biased standard errors and hence to biased statistical significance (Hoffman, 2015). Therefore, it is necessary to take this time dependency, arising while using repeated observations of the same individual, into account.

6.2.2 Standard Longitudinal Multilevel Models

Longitudinal data can be analyzed using MLM, as it can be classified as hierarchical data (Hoffman, 2015).[68] The application of MLM to analyze longitudinal data has several advantages, whereas most of them going back to the general advantages of MLM. One advantage is the flexibility in modeling the dependency of longitudinal data. MLM takes the dependency due to repeated observations into account by treating the variance of the intercept and/or the slope as random and hence allows each individual to have his or her own random intercept and/or slope (Hoffman, 2015). Another advantage is the opportunity to include independent variables on multiple levels of the longitudinal data analysis (Hoffman, 2015). Thereby, the independent variables can be categorical variables or continuous variables, or even both. In addition, interaction terms[69] can be included easily (Hosoya et al., 2014) and not only interaction terms between variables within a level, but also interaction terms with variables between levels, so called cross-level interactions can be included (Hoffman, 2015). Furthermore, MLM can easily be used with unbalanced data, because while using MLM it is not necessary to exclude individuals from the analysis which are not observed over the whole time (Hoffman, 2015).

The hierarchical structure of longitudinal data represented by occasions, which are nested within individuals, leads to a multi-level model with occasions at level-1 and individuals at level-2. This nested data structure of longitudinal data is exemplarily displayed in Figure 7 for two individuals (Individual_1 and Individual_2) at level-2 and different occasions at level-1 (t_1, t_2 and t_3 as well as t_4, t_5 and t_6).

[68] Of course there are also other methods to analyze longitudinal data, but with respect to the later combination of longitudinal and dyadic data only MLM will be presented here. For more information on further methods for longitudinal data analysis see Wooldridge (2010) or Frees (2004).

[69] In general, interaction effects are considered, when it is assumed that the effect of an independent variable on the dependent variable is moderated by another variable, the moderator variable. The effect of an independent variable on the dependent variable is assumed to vary as a function of the moderator variable (Jaccard and Turrisi, 2003). The concept of interaction terms in MLM is the same as in Multiple Regression Analysis (Hoffman, 2015).

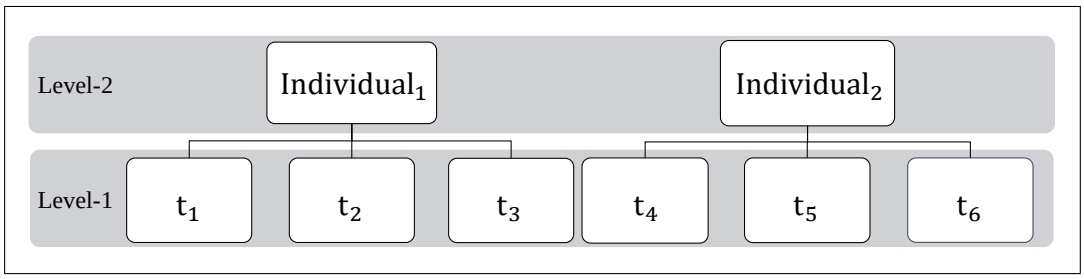

Figure 7: Nested Data Structure of Longitudinal Data.
(Source: Own presentation according to Skrondal and Rabe-Hesketh (2008).)

It is displayed that Individual_1 is observed at occasion t_1, occasion t_2 and occasion t_3 and Individual_2 is observed at occasion t_4, occasion t_5 and occasion t_6. Because the individuals are observed at different occasions and not each individual is observed at each occasion, Figure 7 exemplarily displays the nested structure of an unbalanced longitudinal sample.[70]

In such a two-level model, the within-person variation and therefore the difference from the individual baseline level is modeled at level-1. The between-person variation and hence the difference between individuals is modeled at level-2 (Hoffman, 2015). As already mentioned, using MLM, the intercept and/or the slope will additionally be estimated by a function of a fixed and a random part at an upper level. Thereby, different models can be estimated considering longitudinal data: A Random-Intercept-Only Model, a Random-Intercept Model and a Random-Intercept-Random-Slope Model (Raudenbush and Bryk, 2002; Hosoya et al., 2014; Hoffman, 2015).

A Random-Intercept-Only Model

First, there is the Random-Intercept-Only Model, which primarily serves the purpose to identify the extent of dependency arising because of the repeated measurement of the particular individuals (Hosoya et al., 2014). Equation (1) and Equation (2) represent the Random-Intercept-Only Model.

Level 1 Occasions:

$$Y_{ti} = \beta_{0i} + \epsilon_{ti} \tag{1}$$

Level 2 Individuals:

$$\beta_{0i} = \gamma_{00} + \delta_{0i} \tag{2}$$

Considering level-1, the dependent variable Y_{ti} at time t for individual i is defined as an intercept β_{0i} for individual i and an occasion- and subject-specific

[70] In a figure of a nested structure of a balanced longitudinal sample, all individuals would be measured at the same occasions.

level-1 residual ϵ_{ti} at time t for individual i. Level-2 presents the equation for the intercept β_{0i} which consists of a fixed part γ_{00} as well as a random part δ_{0i}. Thereby, the fixed part γ_{00} displays the grand mean of the individual means and the random part δ_{0i} the individual-specific deviation between the grand mean and each individual mean over time (Raudenbush and Bryk, 2002; Hosoya et al., 2014; Hoffman, 2015).[71]

To determine the degree of the dependency within an individual, arising by repeated measurements of longitudinal data, the Intraclass Correlation Coefficient (ICC) can be calculated after the estimation of Equation (1) and Equation (2). The ICC presents the composition of the variance in Y_{ti} (Hosoya et al., 2014; Hoffman, 2015; Frees, 2004) and hence shows the proportion of variance in Y_{ti}, which is due to constant mean differences between individuals (between-person variance of δ_{0i}). This means that 1-ICC represents the proportion of variance in Y_{ti}, which is due to the variation around those individual means (within-person variance of ϵ_{ti}). The extreme ICC value of 0 would express that there is no degree of dependency within an individual. However, the other extreme ICC value of 1 would represent that all the variance in Y_{ti} is due to constant mean differences between individuals. Based on the Random-Intercept-Only Model, the ICC can be calculated as the ratio of the between-individual variance (BI Variance) to the total variance represented by the sum of between-individual variance (BI Variance) and within-individual variance (WI Variance) (Hoffman, 2015):

$$ICC = \frac{(\text{BI Variance})}{(\text{BI Variance} + \text{WI Variance})} \tag{3}$$

The ICC calculated in a Random-Intercept-Only Model not only identifies the extent of dependency in the used data, but also assists with the decision whether the underlying data should be estimated using a Non-Nested Model or a Nested Model (Wenzelburger et al., 2014; Hoffman, 2015). In previous literature, the use of a multilevel model and hence a Nested Model instead of a model with no different levels is recommended from an ICC greater than 0.10, respectively greater than 10% (Lee, 2000; Killip et al., 2004). If furthermore a significant difference in the model fit between a Nested Model and a Non-Nested Model exists, can be determined by performing a likelihood-ratio test which tests whether the ICC is significantly greater than zero (Hoffman, 2015).

[71] Including Equation (2) into Equation (1), it can be seen that the Random-Intercept-Only Model is very similar to a Fixed-Effects Model, but the two models differ in the assumption about the distribution of the residuals. For more information see Hosoya et al. (2014) or Wooldridge (2010).

The likelihood-ratio test is a statistical test, which compares the goodness of fit of two models. Thereby, it tests the null hypothesis that a Model A fits the data significantly better than a Model B, which is an extension of Model A (Snijders and Bosker, 2012). Therefore, the fit of a Non-Nested Model without a random intercept and the Random-Intercept-Only Model (Nested Model) has to be compared using such likelihood-ratio test. If the test displays that the ICC is significantly greater than zero, the Nested Model fits the data better than the Non-Nested Model. H_0 is rejected (Hoffman, 2015). Additionally, the models can be compared using the Akaike Information Criterion (AIC), the Bayesian Information Criterion (BIC) and the -2 log likelihood (-2LL) value. The AIC, the BIC and the -2LL value represent indices for relative model fit. Comparing two models, their values can be used to decide which model approximates the data best. Thereby, smaller values in terms of less positive or more negative represent a better model fit (Burnham and Anderson, 2004; Kuha, 2004; Hoffman, 2015).

A Random-Intercept Model

To analyze the effect of one or more independent variables on a dependent variable in a Nested Model, a Random-Intercept Model can be estimated. A Random-Intercept Model represents an expansion of the Random-Intercept-Only Model by an independent variable or independent variables at level-1 or at level-2 (Hosoya et al., 2014). Thereby, independent variables, which are time-varying and occasion-specific or occasion- and subject-specific, have to be included into the model at level-1 where the within-person variation is modeled. Independent variables, which are constant over time but different for the particular individuals, are included at level-2 where the between-person variation is modeled (Hosoya et al., 2014). Equation (4) and Equation (5) exemplarily represent such a model with a time-varying independent variable X_{1ti} at level-1, as well as a constant independent variable Z_{1i} at level-2.

Level-1 Occasions:

$$Y_{ti} = \beta_{0i} + \beta_{1i} X_{1ti} + \epsilon_{ti} \tag{4}$$

Level-2 Individuals:

$$\begin{aligned} \beta_{0i} &= \gamma_{00} + \gamma_{01} Z_{1i} + \delta_{0i} \\ \beta_{1i} &= \gamma_{10} + \gamma_{11} Z_{1i} \end{aligned} \tag{5}$$

Like in the Random-Intercept-Only Model, the dependent variable at time t for individual i is displayed by Y_{ti} at level-1. However, Y_{ti} in the Random-Intercept Model is represented by the intercept β_{0i} and a coefficient β_{1i} of the

time-varying variable X_{1ti} at time t for individual i. The occasion- and subject-specific level-1 residual ϵ_{ti} remains. While using the Random-Intercept Model, the assumption is made that there is a random intercept for the different individuals, but that the effect of the independent variable at level-1 is the same for all individuals at level-2. Hence, individuals at level-2 have a random intercept, but the slopes are the same for all individuals. This is represented in Equation (5). The equation of the intercept β_{0i} at level-2 consists of a fixed part γ_{00}, the coefficient γ_{01} of the constant independent variable Z_{1i} for each time and individual i as well as a random part δ_{0i}. The random part again displays the individual-specific deviation from the estimated grand mean. The coefficient β_{1i} however equals a fixed part γ_{10} and the coefficient γ_{11} of the constant independent variable Z_{1i}. Therefore, β_{1i} is explained by only a fixed and no random part.

Random-Intercept-Random-Slope Model

If it is considered that the effect of an independent variable also differs within the individuals at level-2, a Random-Intercept-Random-Slope Model has to be estimated including a random part in the equation for the regression coefficient of the independent variable at level-2 of the Random-Intercept Model. Such a Random-Intercept-Random-Slope Model is represented in Equation (6) and Equation (7).[72]

Level-1 Occasions:

$$Y_{ti} = \beta_{0i} + \beta_{1i} X_{1ti} + \epsilon_{ti} \tag{6}$$

Level-2 Individuals:

$$\begin{aligned} \beta_{0i} &= \gamma_{00} + \gamma_{01} Z_{1i} + \delta_{0i} \\ \beta_{1i} &= \gamma_{10} + \gamma_{11} Z_{1i} + \nu_{1i} \end{aligned} \tag{7}$$

The dependent variable Y_{ti} is still represented by an intercept β_{0i} and the coefficient β_{1i} of the time-varying variable X_{1ti} as well as the occasion- and subject-specific level-1 residual ϵ_{ti}. Also the intercept β_{0i} at level-2 is still represented by a fixed part γ_{00}, the coefficient γ_{01} of the constant independent variable Z_{1i} and the random part δ_{0i}. However, β_{1i} is now not only represented by the fixed part γ_{10} and the coefficient γ_{11} of the constant independent variable Z_{1i}, but also by a random part displayed by ν_{1i}. Hence, the coefficient β_{1i}

[72] Including Equation (2) into Equation (1) it can be seen that the Random-Intercept-Random-Slope Model is very similar to a Random-Effects Model. For more information see Hosoya et al. (2014) or Wooldridge (2010).

at level-2 now also consists of a random part, which indicates that the effect of the independent variable X_{1ti} at level-1 differs within the individuals at level-2 (random slope).

Comparing the three presented models, the Random-Intercept-Only Model primarily serves the purpose of identifying the extent of dependency and is estimated to decide whether a nested or a Non-Nested Model should be considered. If a Nested Model is selected, the Random-Intercept Model and the Random-Intercept-Random-Slope Model can be used to identify relationships between different independent variables and a dependent variable, because time-varying independent variable as well as a constant independent variable are provided. To figure out, whether a Random-Intercept Model, considering random intercepts or a Random-Intercept-Random-Slope Model, considering random intercepts and random slopes is better suited to estimate a certain relationship and hence which of these two models fits the underlying data better, the relative model fit indices, the AIC, the BIC and the -2LL value can be compared and the likelihood-ratio test can be performed (Wenzelburger et al., 2014; Hoffman, 2015).

6.3 Multilevel Modeling of Dyadic Data

6.3.1 Peculiarity of Dyadic Data

While using data of couples, called dyadic data, it is important to take the specific characteristics of such data into account. Data of two individuals is always dyadic data, independent of the context. Examples are dating or marital partners, a mother and a child, siblings or a doctor and a patient (Kenny et al., 2006). Thereby, the individuals are nested within a dyad, which makes dyadic data to ba a specific case of group data, whereby the group only consists of two members. Therefore, dyadic data represents nested data like students in a classroom or a wife and a husband within a married couple (Kenny et al., 2006). Dyadic data can appear by voluntary linkage, for example as in friendships or by kinship linkage as in families, for example parents and children or cousins. Then, there are opportunities of experimental linkage or of yoked linkage. Experimental linkage arises if individuals are randomly paired off in laboratory. Yoked linkage however results if individuals share a certain contextual or environmental event (Kenny et al., 2006; Thomas, 2016). Often dyads arise by a combination of these types of linkages (Kenny et al., 2006).

A dyad is characterized by interpersonal interactions and interpersonal relations, which means that observations are not only related to a single individ-

ual, but also to both individuals within a dyad, integrated in a social context (Kenny et al., 2006). Hence, the observations of a dyad are non-independent because the observations of two members of a dyad are more similar to one another than two observations of two individuals that are not within the same dyad (Kenny et al., 2006). Even if statistical similarity occurs more often, there is also the possibility of dissimilarity, called negative non-independence (Kenny et al., 2006). In this case, the observations of two members of a dyad are more dissimilar to one another than two observations of two individuals that are not within the same dyad.[73] Non-independence can be regarded as a correlation between observations. Thereby, a positive correlation represents similarity and a negative correlation dissimilarity (Kenny et al., 2002).

Kenny (1996) and Kenny and Judd (1986) identify four sources, through which non-independence in dyads may arise: a compositional effect, partner effects, mutual influence and common fate. The first source, the compositional effect, is an effect of similarity before matching. This effect refers to assortative matching which describes that individuals with one or more similar characteristic tend to link together (Becker, 1973, 1974, 1991; Watson et al., 2004, 2014; Siow, 2015). In this field of research, it can for example be found that individuals with similar characteristics like age or education are more likely to marry each other (Vandenberg, 1972; Domingue et al., 2014). If non-independence arises while the characteristics, features or behavior of an individual influence the outcome of another individual, it is called partner effect (Kenny, 1996). An example for a partner effect is that the unemployment of a husband (feature of the husband) has a negative effect on the life satisfaction of his wife (outcome of the wife) (Marcus, 2013). The mutual influences however describe the influence between outcome variables of individuals, for example if a husband's life satisfaction influences the life satisfaction of his wife (Kenny, 1996). Another example for mutual influence is the influence of the perception of sympathy while meeting a stranger. If two strangers get to know each other, the perception of each other in turn depends on each other - the more one of these individuals likes the other one, the more this individual likes the individual in return. Therefore, there is a process of feedback associated with mutual influence (Kenny et al., 2006). Furthermore, common fate can cause non-independence by external factors influencing both individuals. Examples for such external factors are climate (Kenny, 1996) and the social or legal order.

Because of the statistical consequences, arising due to the non-independence of

[73] Negative non-independence may arise by four factors: compensation, social comparison, zero sum or division of labor. For further readings see (Kenny et al., 2006).

dyadic data, it is important to consider this specific characteristic of the data while using dyadic data. Standard statistical procedures assume independent observations, thus ignoring the non-independence of dyadic data and treating them as independent will result in diverse consequences. Like mentioned for nested data in general, ignoring this specific structure leads to biased variances that affect the standard errors of test statistics and in turn result in biased statistical significance. Especially the non-independence of dyadic data biases the degrees of freedom in the test of significance, because information is provided by both individuals in a dyad, which falsely leads to two data points (Kenny and Judd, 1986; Kenny et al., 1998, 2006).

Next to the non-independence of dyadic data, another characteristic of dyadic data also influences the choice of the statistical method used to analyze such data, the characteristic of the distinguishability of the members of a dyad. Using dyadic data, it can be differentiated between dyads with distinguishable members or dyads with indistinguishable members[74] (Gonzalez and Griffin, 1999; Kenny et al., 2006; Ackerman et al., 2012). In a dyad with distinguishable members, the two members of the dyad can be differentiated by a certain character and the possibility of a systematic order of the respective scores is given (Kenny et al., 2006; Ackerman et al., 2012). They belong to the same class or category (Gonzalez and Griffin, 1999). Examples for dyads with distinguishable members are heterosexual couples like wife and husband or girlfriend and boyfriend with the distinguishable characteristic gender. Other examples are an employer and an employee as well as a teacher and a student, distinguishable by their position. A further example is a parent and a child, separable by their family role. In dyads with indistinguishable members, it is not possible to differentiate between the two members for example in a dyad with two co-workers or in same-sex couples (Kenny et al., 2006). In dyads with indistinguishable members, the two members of the dyad do not belong to the same, but to different classes or categories (Gonzalez and Griffin, 1999).[75]

Ackerman et al. (2012) divide distinguishability in conceptual and empirical distinguishability. Conceptual distinguishability is given, if the members of a dyad can be systematically classified by some variables. However, empirical distinguishability is given, if indeed some differences in the data exist. Related to this, Kenny et al. (2006) recommend that the distinguishing characteristic or variable should be theoretically or empirically meaningful. Gonzalez and Griffin (1999) however promote to differentiate between dyads with dis-

[74] Also named as dyads with exchangeable members, see Gonzalez and Griffin (1999).

[75] For more examples on dyads with distinguishable members and dyads with indistinguishable members see Kenny et al. (2006).

tinguishable members or dyads with indistinguishable members by theoretical assumptions rather than empirical tests.[76]

While using dyadic data, a distinction can also be made between three types of variables, between-dyads variables, within-dyads variables and mixed variables. Between-dyads variables are those variables which have different scores from dyad to dyad, but the same score for both members of the dyad (Kenny et al., 2006). An example for a between-dyads variable is the length of a couple's marriage (Kenny et al., 2006), both members of the dyad, the wife and the husband, having an identical length of their marriage, but the length of the marriage of another dyad may be different. Another example is the number of children in a dyad of parents, or gender in same-sex friendships when dyads with men and dyads with women are considered.

Within-dyads variables are variables having different scores within a dyad but the same average score for each dyad. Therefore, the two members of a dyad have a different score of the within-dyads variable but the average of the scores of the two members is identical for each dyad. Gender is an example for a within-dyads variable when heterosexual couples are considered. Each member of a dyad is either a woman or a man, and all dyads are composed of both genders. The family role is also a within-dyad variable if dyads of a parent and a child are considered (Kenny et al., 2006).

Whereas between-dyads variables describe variation between dyads and within-dyads variables variation within dyads, mixed variables are variables, which vary between and within dyads. Considering a study of married couples, age may be a mixed variable because the age of the wife and the husband within one dyad may be different and the average age of another couple could be different, as well (Kenny et al., 2006). Another example for a mixed variable in dyads of married couples is the personnel labor income. Both members have different labor incomes and the average income of a dyad also differs between dyads. In contrast to this, the household income in married couples is a between-dyads variable because it has the same amount for both spouses, but it differs between dyads. It is important to note that depending on the context, a variable can be classified as a between-dyad variable, a within-dyad variable or a mixed variable (Kenny et al., 2006). As the presented examples have already shown, the classification of a variable must always be made individually with reference to the study design.

[76] Hereinafter, it is focused on dyads with distinguishable members because the analysis concentrates on heterosexual couples and gender was theoretically identified as a meaningful distinguishing variable in Chapter 3.2.

6.3.2 Actor-Partner Interdependence Model

To take into account the non-independence of dyadic data, especially with regard to non-independence due to partner effects (Kenny and Cook, 1999), an APIM can be used to analyze dyadic data (Kenny et al., 2006; Becker and Lois, 2015). The APIM is a statistical model that considers the influence of dyad members among each other and is able to analyze mixed independent variables and hence variables that vary within and between dyads. It allows to measure interdependence within interpersonal relationships and produces outcomes and predictors for both members of a dyad. The APIM is an often-used model to analyze dyadic data. Particularly in the fields of psychology, health and social sciences but also in economic sciences. [77]

While analyzing dyadic data using an APIM, a simultaneous estimation of actor and partner effects is possible. An actor effect is the effect of an individual's own independent variable on the individual's own dependent variable and a partner effect is the effect of an individual's own independent variable on the partner's dependent variable (Kenny et al., 2006; Kenny and Ledermann, 2010).[78]

Figure 8 shows an APIM with actor and partner effects. X_1 and X_2 represent the independent variables of the two members of the dyad, *member 1* and *member 2* and Y_1 and Y_2 the corresponding dependent variables. The actor effect of *member 1* is represented by a_1 hence, the effect of the independent variable of *member 1*, X_1, on the dependent variable of *member 1*, Y_1. The partner effect from *member 1* to *member 2* is represented by $p_{1\,to\,2}$, from the independent variable of *member 1* to the dependent variable of *member 2*. Accordingly, a_2 and $p_{2\,to\,1}$ represent the actor and partner effect for dyad *member 2*.

The line between the independent variables, X_1 and X_2 of *member 1* and *member 2* displays a correlation between these variables. Accordingly, a correlation between the characteristics or certain extents of the two members of a

[77] Kenny and Ledermann (2012) give an overview of all articles using an APIM for analysis up to 2012. They identify 433 articles. A following database research for articles after 2012 until 2017 in the economic databases Business Source Premier, EconLit and Econbiz results in additional 48 articles. Furthermore, it was searched in three additional databases PsycINFO, PubMed and Scopus, because the focus of the usage of the APIM is in the field of psychology, health and social sciences. In these databases further 353 articles could be identified. In all databases it was searched for the keyword „Actor-Partner-Interdependence Model". The results were restricted to be published between 2013 and 2017, written in English and peer reviewed. Duplicate articles were excluded. Version of March 2017.

[78] It is concentrated on the APIM for dyads with distinguishable members. In this case there are two actor effects and two partner effects. For more information on the APIM for dyads with indistinguishable members see Kenny et al. (2006).

dyad may perhaps exist because of compositional effects (Kenny et al., 2006). As described previously, a compositional effect is an effect of similarity before matching, the correlation may be due to a similarity of the two dyad members before they were examined together using an APIM. Additionally, this correlation ensures that the effects of the independent variables on the dependent variables are estimated while controlling for the other independent variable, respectively (Cook and Kenny, 2005). Figure 8 also shows a second correlation between the residuals E_1 and E_2 (Kenny et al., 2006). Because residuals represent the unexplained variance in the dependent variables Y_1 and Y_2, the correlation between E_1 and E_2 constitutes the non-independence, which can not be explained by the APIM (Kenny and Cook, 1999; Kenny et al., 2006).

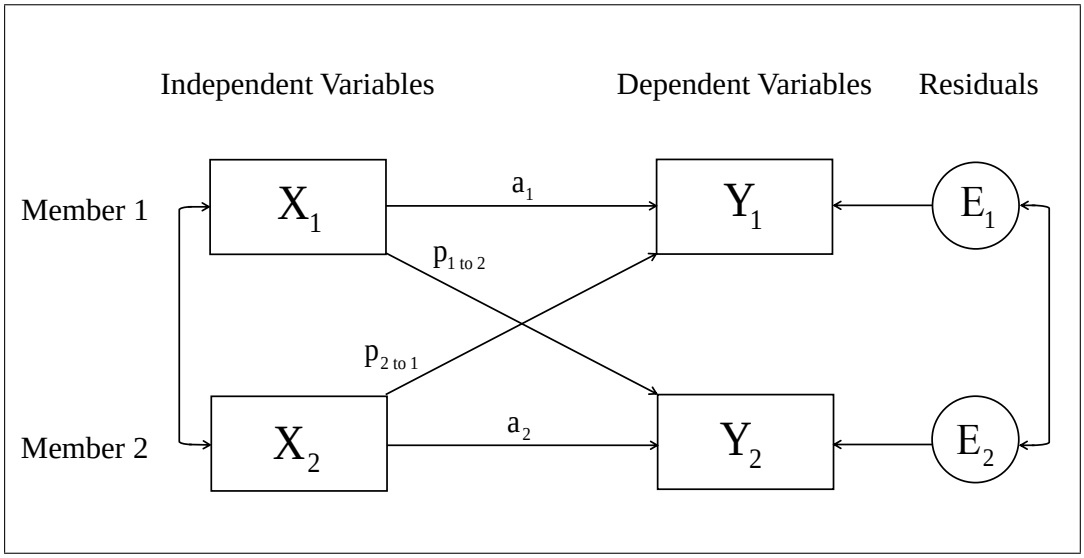

Figure 8: Actor-Partner Interdependence Model for Dyads with Distinguishable Members.
(Source: Own presentation according to Kenny et al. (2006).)

Two-Level Modeling of an APIM

An APIM can be estimated using MLM as the underlying dyadic data is hierarchical, where units are nested within another (Cook and Kenny, 2005; Kenny et al., 2006; Becker and Lois, 2015).[79] More specifically, considering dyadic data, individuals are nested within dyads. This nested structure leads

[79] Another method to estimate an APIM is the Structural Equation Modeling (SEM). However, SEM is not used here, because it is particularly applied when latent variables should be estimated or if the independent variables consist of measurement errors (Kenny et al., 2006). Both cases do not exist in the present analysis. Furthermore, MLM provides some advantages over SEM. MLM is the more flexible estimation approach regarding the underlying data. Contrary to SEM, MLM can easily used with unbalanced data and it directly provides the estimations and tests of actor effects and partner effects (Kenny et al., 2006; Hoffman, 2015).

to a multi-level model with individuals at level-1 and dyads at level-2 (Kenny et al., 2006). Alternatively, considering the vocabulary of the APIM, a group of an actor and his partner is examined, so the level-1 unit is the actor or the partner and the level-2 unit is the group of an actor and a partner. Figure 9 exemplarily represents this nested structure of dyadic data for two dyads at level-2 and the actor and partner of each dyad at level-1.

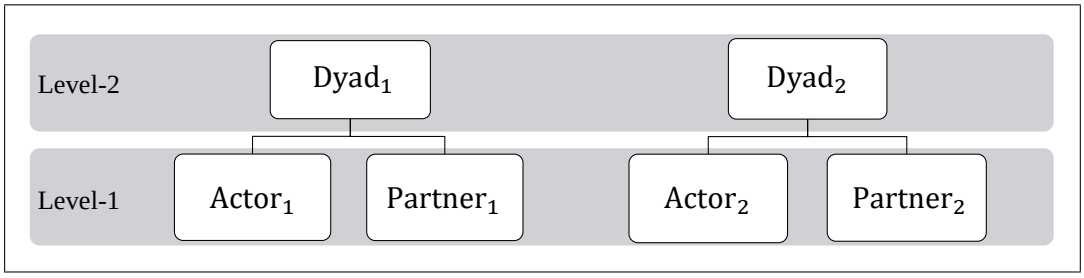

Figure 9: Nested Data Structure of Dyadic Data.
(Source: Own presentation.)

All variables, which are included in an APIM, are related to one of the levels represented in Figure 9 (Kenny et al., 2006). The dependent variable is always a level-1 variable, because it is always related to an individual. The independent and the control variables can however either be related to the individual-level (level-1) or to the dyad-level (level-2) (Kenny et al., 2006). For example, in a married couple, a level-1 variable would be the life satisfaction of the wife or the husband and a level-2 variable the household income. This example shows that a level-2 variable always has the same score for the individuals from level 1. Therefore, it is always a between-dyads variable (Kenny et al., 2006).

To estimate the APIM with a multilevel approach, the used dyadic data has to be organized pairwise. This means each individual is represented twice in the dataset. The outcome score of one individual is always associated with his own predictor scores and the predictor scores of his or her partner (Kenny et al., 2006; Becker and Lois, 2015). Thereby, each individual is treated as one case and there are always two cases per dyad (Kenny et al., 2006). Thereby, the individuals, which are within the same dyad, tend to be more similar to each other than individuals from other dyads, representing the non-independence of dyadic data (Kenny et al., 2006; Rabe-Hesketh and Skrondal, 2012).

Generally, MLM takes the non-independence within a group or cluster into account by treating the variance of the intercept and/or the slope between groups or clusters as random. Therefore, the intercept and/or the slope will additionally be estimated by a function of a fixed and a random part. Thereby,

the fixed part represents the grand mean of the intercept or the slope over all groups or clusters and the effects of upper-level variables (Kenny and Kashy, 2011; Becker and Lois, 2015). Using MLM for dyads, respectively groups or clusters with only two members, there are not enough lower-level units (just two members per dyad) allowing the slopes to vary randomly. Hence, in the dyad case, the variance of the slopes are not treated as random but are estimated by a function of a fixed part (Kenny and Kashy, 2011; Becker and Lois, 2015). Accordingly, an APIM is estimated using MLM with the following equations (Kenny and Kashy, 2011):

Level-1 Individuals:

$$\begin{aligned} Y_{ij} = \beta_{0j} + \beta_{1j} XA_{ij} + \beta_{2j} XP_{ij} + \beta_{3j} DV_{ij} + \\ \beta_{4j} DV_{ij} XA_{ij} + \beta_{5j} DV_{ij} XP_{ij} + \epsilon_{ij} \end{aligned} \tag{8}$$

Level-2 Dyads:

$$\begin{aligned} \beta_{0j} &= \gamma_{00} + \gamma_{01} Z_j + \delta_{0j} \\ \beta_{1j} &= \gamma_{10} + \gamma_{11} Z_j \\ \beta_{2j} &= \gamma_{20} + \gamma_{21} Z_j \\ \beta_{3j} &= \gamma_{30} + \gamma_{31} Z_j \\ \beta_{4j} &= \gamma_{40} + \gamma_{41} Z_j \\ \beta_{5j} &= \gamma_{50} + \gamma_{51} Z_j \end{aligned} \tag{9}$$

The dependent variable of individual i of dyad j is represented by Y_{ij}. The independent variables are represented by XA_{ij} and XP_{ij}, where XA_{ij} represents the individual's own record and XP_{ij} the partner's record. Therefore, the level-1 equation contains actor and partner effects. DV_{ij} displays the distinguishing variables, which differentiate the two members of a dyad. Additionally, interaction terms between the actor effect, respectively the partner effect and the distinguishing variable ($DV_{ij}XA_{ij}$ and $DV_{ij}XA_{ij}$) are included in the level-1 equation as the effects may differ as a function of the distinguishing variable. Finally, e_{ij} displays the residual for individual i within dyad j. The level-2 equations contain the upper-level and hence the dyad level variable, represented by Z_j. The first level-2 equation is the estimation of the intercept of level-1, which contains a fixed and a random part. The equations below represent the estimations of the slopes of the level-1 variables, consisting only of a fixed part (Kenny and Kashy, 2011).[80]

[80] For a description of the estimation of the APIM using MLM in the indistinguishing case, see Kenny and Kashy (2011).

Considering the non-independence of the data, it should be taken into account that the residual variances may not be the same for both members of the dyad. Perhaps the unexplained variance in the dependent variable may differ across the levels of the distinguishing variable. Therefore, a heterogeneous compound symmetry should be assumed that allows for heterogeneous variances as a function of the distinguishing variable (Kenny and Kashy, 2011). The compound symmetry structure models the non-independence between the members of a dyad as a covariance rather than a variance and hence negative non-independence can be represented as well (Kenny and Kashy, 2011; Becker and Lois, 2015).

The non-independence of the dyadic data and hence the dependency between the members within a dyad can be measured within the estimation of the APIM using the ICC.[81] As already presented, using MLM for longitudinal data, the ICC is represented by the ratio between the variance within a level and the total variance (Becker and Lois, 2015). However, using this measurement, the ICC can take only positive values, so Kenny et al. (2006) recommend to estimate the ICC while using dyadic data as follows:

$$ICC_{DyadicData} = \frac{(\text{BD Variance} - \text{WD Variance})}{(\text{BD Variance} + \text{WD Variance})} \tag{10}$$

Regarding Equation 10, *BD Variance* displays the variance between dyads and *WD Variance* the variance within a dyad. This measurement of the ICC ensures that positive non-independence as well as negative non-independence can be represented by the ICC (Becker and Lois, 2015). Thereby, the interpretation of the ICC remains the same.

6.4 Empirical Approach for Multilevel Modeling of Longitudinal Dyadic Data of Job Insecurity and Mental Health

The data used to analyze the spillover and crossover effects of job insecurity to the mental health status combines the specific characteristics of dyadic and longitudinal data presented in Chapter 6.2.1 and Chapter 6.3.1. This longitudinal dyadic data is characterized by dependency due to interpersonal relations and due to repeated observations, since individuals within dyads are followed up over some years. Hence, the data contains two types of non-independence,

[81] For distinguishing dyads, it is also possible to measure the non-independence by using a Pearson product-moment correlation coefficient (Kenny et al., 2006).

within-individuals and within-dyads, which have to be taken into account while analyzing such longitudinal dyadic data. To develop an empirical approach for MLM of longitudinal dyadic data, the MLM for longitudinal data represented in Chapter 6.2.2 and the MLM of dyadic data presented in Chapter 6.3.2 has to be taken into account and will be united in the following with regard to longitudinal dyadic data of job insecurity and mental health.

The dependent variable of the present analysis, the mental health status of an individual, is a mixed variable which varies between- and within-dyads. The mental health status varies by time and individual and is therefore an occasion- and subject-specific time varying variable. The independent variable, job insecurity, can be classified as a mixed-variable, which is time varying and occasion- and subject-specific. The variable takes different values for the members within a dyad and a different average compared to other dyads. Additionally, this variable varies by time and individual. However, the independent variable measuring gender is a within-dyads variable, because gender displays different scores within a dyad, but the same average score for each dyad. Furthermore, it is a constant variable, which does not change over time.[82] The control variables measuring age, education and occupation are also mixed-variables and hence vary between- and within-dyads. They are time varying and occasion- and subject-specific because they (can) display different values for the members within a dyad and a different average compared to other dyads for the different occasions.

Over-time Standard Actor-Partner Interdependence Model

Taking into account the dependency due to interpersonal relations as well as the variable types of the dependent, independent and the control variables, an APIM can be used to analyze the spillover and crossover effects of job insecurity. Considering the dependency arising due to the repeated observations supplementary, it is however not possible to estimate the APIM presented in Chapter 6.3.2 for dyadic data. The APIM has to be expanded for longitudinal dyadic data, as the repeated measurements of the variables have to be represented by the model, as well. An Over-time Standard APIM represents such an expansion, which in addition to the dyadic character also involves the longitudinal character of longitudinal dyadic data by taking the point in time of measurement into account (Kenny et al., 2006).

Similar to an APIM, the Over-time Standard APIM is estimated differently for dyads with distinguishable and indistinguishable members. Hence, while using

[82] Gender transformations are excluded, because the underlying data shows no case of gender transformation in the selected sample.

the Over-time Standard APIM for the longitudinal dyadic data of job insecurity and mental health, gender should not only be theoretically (Chapter 3.2), but also empirically identified as a meaningful distinguishing variable. This can be done by comparing two Over-time Standard APIMs using a likelihood-ratio test. One Over-time Standard APIM, treating the dyad members as distinguishable and another Over-time Standard APIM, treating them as indistinguishable (Kenny et al., 2006). When the Over-time Standard APIM with distinguishing members performs better, it can be confirmed empirically that gender is a meaningful distinguishing variable (Kenny et al., 2006). As a consequence, an Over-time Standard APIM with two actor effects and two partner effects can be considered. More specifically, an Over-time Standard APIM with interaction terms similar to the APIM presented in Chapter 6.3.2 for dyadic data can be used.[83] Such an Over-time Standard APIM for longitudinal dyadic data of job insecurity and mental health is displayed in Figure 10.

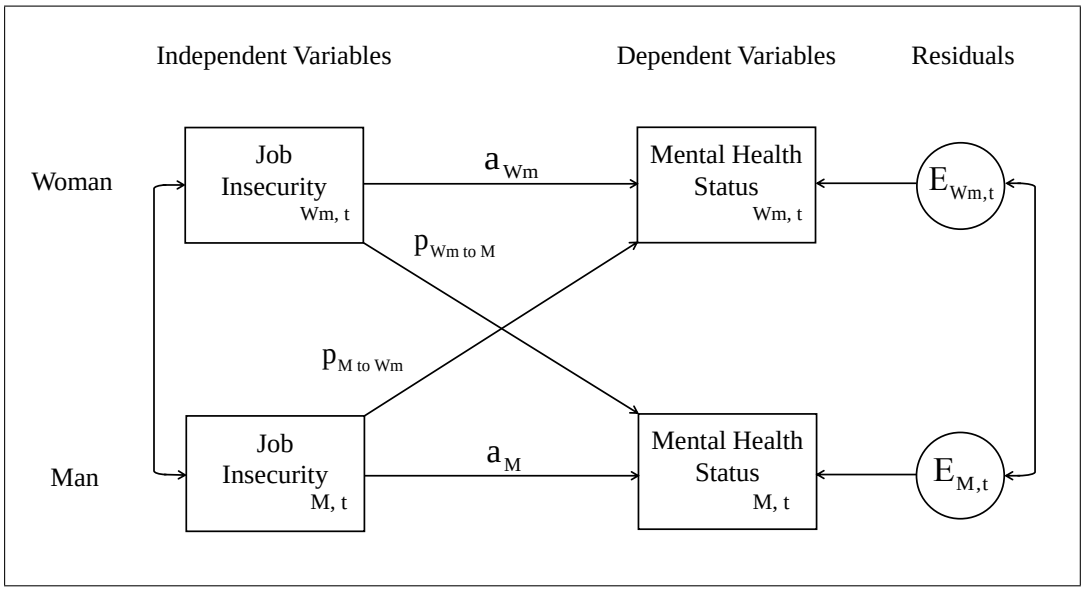

Figure 10: Over-time Standard Actor-Partner Interdependence Model for Job Insecurity and Mental Health.
(Source: Own presentation according to Kenny et al. (2006).)

The important difference between the Over-time Standard APIM for longitudinal dyadic data and the APIM from Chapter 6.3.2 for dyadic data is the included time-index, which can be seen in the specific Over-time Standard APIM for job insecurity and mental health in Figure 10. The time-index is represented by t with t =*2002, 2004, 2006, 2008, 2010, 2012*. In its fundamentals, the Over-time Standard APIM does not consider a lagged time-index

[83] In the following, it should be assumed that the members of the dyads are distinguishable by gender.

(Kenny et al., 2006). However, such a case would be conceivable and useful especially with regard to temporal asymmetry between independent and dependent variables to detect causal relationships. Nevertheless, for the general presentation of an Over-time Standard APIM, actor and partner effects of job insecurity on the mental health status are considered at the same points in time. Furthermore, at the moment no theoretically driven causes lead to a lagged consideration of job insecurity and mental health. Methodological causes for a lagged consideration should therefore be considered after empirical evidence for the fundamental Over-time Standard APIM is detected.

The actor and partner effects in the Over-time Standard APIM of Figure 10 and hence the spillover and the crossover of job insecurity to the mental health status, are differentiated for women (Wm) and men (M) at time t. The actor effect for women is displayed with a_{Wm}. Particularly, a_{Wm} displays the spillover effect of women's job insecurity (Job Insecurity$_{Wm,t}$) at time t on the women's own mental health status (Mental Health Status$_{Wm,t}$) at time t. The spillover effect for men is respectively presented by the effect a_M from men's job insecurity (Job Insecurity$_{M,t}$) at time t on the men's mental health status (Mental Health Status$_{M,t}$) at time t. The partner effect for women is represented by p_{MtoWm} and shows the crossover effect of men's job insecurity at time t to women's mental health status at time t. The arrow which is marked with p_{WmtoM} represents the crossover of job insecurity to the mental health status from women to men respectively. The residuals for women and men at time t are presented by $E_{Wm,t}$ and $E_{M,t}$.

Three-Level Modeling of an Over-time Standard APIM

Like the APIM for dyadic data, the Over-time Standard APIM for longitudinal dyadic data can be estimated using MLM, because longitudinal data has a hierarchical structure as well (Kenny et al., 2006). The sample used for the analysis is furthermore an unbalanced sample, which can easily be handled by MLM (Hoffman, 2015). As explained in Chapter 6.3.2, dyadic data has a hierarchical structure, where individuals are nested within dyads which leads to a multilevel model with two levels, individuals at level-1 and dyads at level-2 (Kenny et al., 2006). If it is now additionally taken into account that such dyads are observed over time, there are three different levels of analysis which have to be considered: levels for occasions, individuals and dyads. Conceptually, this leads to a multilevel model with three-levels, where occasions are assumed to be nested within individuals and again individuals are assumed to be nested within dyads. Hence, a model with occasions at level-1, individuals at level-2 and dyads at level-3 has to be examined (Bolger and Laurenceau, 2013). Such

a three-level model of longitudinal dyadic data is exemplarily represented in Figure 11 for two dyads ($Dyad_1$ and $Dyad_2$) at level-3 with a male and a female member in each dyad. Male $Member_1$ and Female $Member_1$ at level-2 are within $Dyad_1$. Correspondingly, Male $Member_2$ and Female $Member_2$ at level-2 are within $Dyad_2$. Each member is thereby observed at time t_1, t_2 and t_3 which is represented at level-3.

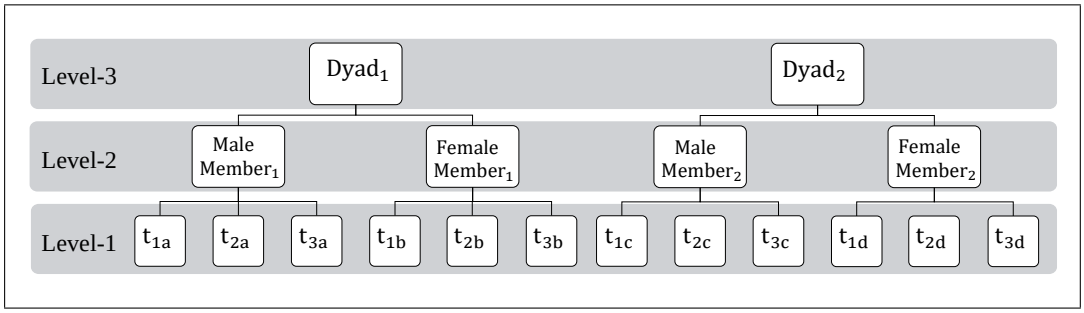

Figure 11: Three-Level Data Structure of Longitudinal Dyadic Data.
(Source: Own presentation according to Bolger and Laurenceau (2013) and Kashy and Donnellan (2012).)

To estimate the actor and partner effects of job insecurity on the mental health status within an Over-time Standard APIM, it is started with developing a conceptually derived three-level model. Therefore, in the beginning the dependency and the nested structure of the data has to be determined. On the one hand the existence of dependency due to repeated observations has to be detected and the proportion of this variance in the mental health status has to be established. On the other hand, it has to be determined if and how much proportion of the variance is due to the dependency because of interpersonal relations. Hence, in a first step, the between-individual, respectively the within-individual variation will be determined and in a second step the between-dyad, respectively the within-dyad variation will additionally be detected (a). In a second step, the three-level model of the Over-time Standard APIM for longitudinal dyadic data of job insecurity and mental health will be drawn up (b).

(a) Determining the Dependency and Nested Structure

To determine the between-individual, respectively within-individual variance in the overall variance of the mental health status in a first step, a Non-Nested Model (linear regression without levels) for the mental health status as dependent variable will be estimated. In this Non-Nested Model, it is assumed that all observations and all individuals are independent. In addition, a Random-Intercept-Only Model with two levels (level-1 occasions, level-2 individuals) for

the mental health status will be estimated. In the two-level Random-Intercept-Only Model, it is assumed that dependency arises due to repeated observations. This dependency can be measured by the ICC representing the proportion of between-individual variation in the mental health status, calculated in the two-level Random-Intercept-Only Model. The proportion of the within-individual variation in the mental health status is however represented by $1 - ICC$ (Wenzelburger et al., 2014; Hoffman, 2015). The two-level Random-Intercept-Only Model will be compared to the Non-Nested Model using the relative model fit indices, the AIC, the BIC and the -2LL value. Additionally, a significant difference between the model fits will be tested using the likelihood-ratio test (Wenzelburger et al., 2014). If the null hypothesis H_0 of the likelihood-ratio test can be rejected, the two-level Random-Intercept-Only Model, assuming occasions to be nested within individuals, fits the data significantly better than the Non-Nested Model (Wenzelburger et al., 2014) and should be used to model the underlying data. This first step determines whether and how much dependency due to the repeated observations is represented in the data. Until now, the dependency due to interpersonal relations is ignored.

Taking also the dependency due to interpersonal relations arising because of the dyadic structure of the data into account, the two-level Random-Intercept-Only Model will be expanded by an additional level in the next step. This leads to a three-level model with occasions at level-1, individuals at level-2 and dyads at level-3, taking the dependency due to repeated observations and the dependency due to interpersonal relations simultaneously into account. Such a model will be estimated and compared to the two-level Random-Intercept-Only Model using the relative model fit indices, the AIC, the BIC and the -2LL value. Additionally, a likelihood-ratio test will be used to compare the three-level Random-Intercept-Only Model with the two-level Random-Intercept-Only Model to determine significant differences between the models. If the null hypothesis H_0 of the likelihood-ratio-test can be rejected, the three-level Random-Intercept-Only Model fits the data significantly better. A rejection of the null hypothesis H_0 shows that there are both types of dependencies represented in the data. Observations of the same individuals are more similar, than observations of different individuals. In addition, observations of two members of a dyad are more similar to one another than are two observations of two individuals not within the same dyad. Based on the three-level model, the proportion of variance in the mental health status at each level can be determined. The level-1 variance (L_1) expresses the within-individual variance (WI Variance), the level-2 variance (L_2) the within-dyad variance (WD Variance) and the level-3 variance (L_3) finally displays the between-dyad variance (BD

Variance). Furthermore, the sum of the level-2 variance and the level-3 variance expresses the between-individual variance (BI Variance). To determine the dependency due to repeated observations within a three-level Random-Intercept-Only Model, the ICC for occasions within individuals within dyads (ICC_{OwIwD}) can be calculated by the following equation (Hoffman, 2015):

$$\begin{aligned} ICC_{OwIwD} &= \frac{(\text{WD Variance} + \text{BD Variance})}{(\text{WI Variance} + \text{WD Variance} + \text{BD Variance})} \\ &= \frac{\text{BI Variance}}{(\text{WI Variance} + \text{BI Variance})} \\ &= \frac{(L_2 + L_3)}{(L_1 + L_2 + L_3)} \end{aligned} \tag{11}$$

The ICC for occasions within individuals within dyads (ICC_{OwIwD}) is expressed by the ratio of the sum of the within-dyad and between-dyad variance to the total variance which in turn consists of the sum of the within-individual, the within-dyad and the between-dyad variance. This expression equals the ratio of the between-individual variance to the sum of the within-individual and between-individual variance. With regard to the variance at the different levels this means that the ICC for occasions within individuals within dyads can be calculated by the ratio of the sum of level-2 and the level-3 variance to the total variance ($L_1 + L_2 + L_3$). The extreme ICC_{OwIwD} value of 0 would express that there is no dependency due to repeated observations. However, the other extreme ICC_{OwIwD} value of 1 would represent that all the variance in Y_{ti} is due to dependency arising because of repeated observations (Hoffman, 2015).

To determine the dependency due to interpersonal relations within a three-level Random-Intercept-Only Model, the ICC for individuals within dyads (ICC_{IwD}) can however be calculated as follows (Hoffman, 2015):

$$\begin{aligned} ICC_{IwD} &= \frac{\text{BD Variance}}{(\text{WD Variance} + \text{BD Variance})} \\ &= \frac{L_3}{(L_2 + L_3)} \end{aligned} \tag{12}$$

Equation 12 shows that the ratio of the between-dyad variance to the sum of the within-dyad variance and the between-dyad variance represent the ICC for individuals within dyads. Considering the designation of different level variances, this means that the ICC for individuals within dyads is expressed

by the ratio of the level-3 variance to the sum of the level-2 and the level-3 variance. The extreme ICC_{IwD} value of 0 would express that there is no dependency due to interpersonal relations in the data. However, the other extreme ICC_{IwD} value of 1 would represent that all the variance in Y_{ti} is due to dependency arising because of interpersonal relations (Hoffman, 2015).

If both ICC values (ICC_{OwIwD} and ICC_{IwD}) are greater than 0.10, respectively 10%, the dependency within the data and the nested structure can be assumed to be given (Lee, 2000; Killip et al., 2004). In combination with the likelihood-ratio test, the dependency and nested structure of the data are empirically determined.

(b) Estimating a Three-Level Over-time Standard APIM

After presenting empirically that the expected dependency exists and that the nested structures are indeed represented in the data, a three-level model of an Over-time Standard APIM of spillover and crossover of job insecurity to the mental health status can be formulated as follows:[84]

Level-1 Occasions:

$$\text{Mental Health}_{tij} = \beta_{0ij} + \beta_{1ij} JIA_{tij} + \beta_{2ij} JIP_{tij} + \beta_{3ij} Time + \epsilon_{tij} \tag{13}$$

Level-2 Individuals:

$$\begin{aligned} \beta_{0ij} &= \gamma_{00j} + \gamma_{01j} Gender_{ij} + \delta_{0ij} \\ \beta_{1ij} &= \gamma_{10j} + \gamma_{11j} Gender_{ij} \\ \beta_{2ij} &= \gamma_{20j} + \gamma_{21j} Gender_{ij} \\ \beta_{3ij} &= \gamma_{30j} + \delta_{3ij} \end{aligned} \tag{14}$$

Level-3 Dyads:

$$\begin{aligned} \gamma_{00j} &= \eta_{000} + \lambda_{00j} \\ \gamma_{01j} &= \eta_{010} \\ \gamma_{10j} &= \eta_{100} + \lambda_{10j} \\ \gamma_{11j} &= \eta_{110} \\ \gamma_{20j} &= \eta_{200} + \lambda_{20j} \\ \gamma_{21j} &= \eta_{210} \\ \gamma_{30j} &= \eta_{300} + \lambda_{30j} \end{aligned} \tag{15}$$

[84] When presenting the model, it is only concentrated on the independent variables. The control variables age, education and occupation would also be included at level-1 as they are time-varying mixed-variables.

Level-1 of the Over-time Standard APIM (Equation 13), representing the occasion level, includes the mental health status ($MentalHealth_{tij}$) as dependent variable at time t of individual i in dyad j. Additionally, all time-varying explanatory variables are included at Level-1 (Krause and Urban, 2013). The mental health status is explained by an intercept β_{0ij}, the independent variable measuring job insecurity and partner's job insecurity as well as by the variable $Time$. The independent variable JIA_{tij} thereby presents the job insecurity dummy variable at time t for individual i in dyad j for an actor and JIP_{tij} respectively for a partner. The variable $Time$ is a continuous variable, measuring the years of observations, which is included to capture time trends. The residual at time t of individual i in dyad j is represented by ϵ_{tij}. Kenny et al. (2006) recommend to model a specific error structure for ϵ_{tij} while estimating dyads over time. Since variables in longitudinal dyadic data are observed over time, the mental health status at time t will be correlated with the mental health status at time $t-1$. To capture this correlation, the residuals should be allowed to be autocorrelated (Kenny et al., 2006).

Level-2 (Equation 14) shows the individual equations for the slopes of the intercept and the independent variables as well as the slope of the variable $Time$. The equation of the slope of the intercept thereby includes a fixed (γ_{00j}) and a random part (δ_{0ij}) as well as the independent variables of the individual level that are not time-varying, here represented by $Gender_{ij}$. The random part of the slope of the intercept (δ_{0ij}) represents the individual-specific deviation from the predicted dyad's intercept (Hoffman, 2015). Furthermore, the interaction between $Gender_{ij}$ and JIA_{tij} and between $Gender_{ij}$ and JIP_{tij} are represented in the level-2 equations to model differences between women and men. This is represented by the equations of the slopes of the independent variables JIA_{tij} and JIP_{tij}, which also include the variable $Gender_{ij}$. Thereby, as described in Chapter 5, $Gender_{ij}$ is a dummy variable coded 1 if an individual is male and 0 if an individual is female. The actor-effect is displayed by β_{1ij}, the coefficient of the independent variables JIA_{tij}, which in turn consist of the coefficients γ_{10j} and γ_{11j} at level-2. Thereby, an actor-effect for men is measured by the coefficients $\gamma_{10j} + \gamma_{11j} * 1$. The actor-effects for women are however measured by $\gamma_{10j} + \gamma_{11j} * 0$ and hence only by γ_{10j}. The partner effect of job insecurity on the mental health status of men is correspondingly represented by the coefficient $\gamma_{20j} + \gamma_{21j}$ ($\gamma_{20j} + \gamma_{21j} * 1$) and the partner effect of job insecurity on the mental health status of women by γ_{20j}

$(\gamma_{20j} + \gamma_{21j} * 0)$.[85] The slope of the variable $Time$ (β_{3ij}) is expressed at level-2 by a fixed part (γ_{30j}) and a random part (δ_{3ij}), whereas the random part represents the individual-specific deviation from the predicted dyad slope of the variable $Time$.

Equation 15 displays level-3 of the Over-time Standard APIM which consists of the individual equation for each coefficient of level-2. The intercepts of the level-2 equations γ_{00j}, γ_{10j}, γ_{20j} and γ_{30j} are expressed at level-3 by a fixed part (η_{000}, η_{100}, η_{200} and η_{300}) which does not differ between occasions, individuals and dyads. Additionally, the intercepts consist of random parts, which are expressed by λ_{00j}, λ_{10j}, λ_{20j} and λ_{30j}, representing random slopes for the intercepts of the level-2 variables. These random slopes enable the intercepts to vary by dyads and hence represent the dyad-specific deviation from the fixed intercept. The coefficients of $Gender_{ij}$ of the level-2 equations γ_{01j}, γ_{11j} and γ_{21j} however are only expressed by a fixed part (η_{010}, η_{110} and η_{210}) indicating no random slopes for the $Gender_{ij}$ coefficients of level-2.

The models presented above will be estimated using Stata version 14. The multilevel models will be estimated using the command *mixed*. As Stata does not allow to model a covariance structure as a lag 1 autoregressive structure suggested by Kenny et al. (2006), the residuals at level-1 are modeled to have an autoregressive structure of the order 1. This allows for a lag 1 autoregressive structure of the random effects at level-1, but not for the random effects at the other two levels.[86] Laurenceau and Bolger (2012) recommend to include elapsed time as an additional within-person predictor, when the software used does not allow such covariance structure, under the assumption that the autocorrelation is due to omitted time trends (Laurenceau and Bolger, 2012). Therefore, a lag 1 autoregressive structure of the random effects at level-1 will be modeled and a variable which captures time trends (represented by $Time$ in Equation 13) will be included to get a covariance structure as similar as possible to the one suggested by Kenny et al. (2006).

Three-Level Data Structure vs. Two-Level Data Structure

Although longitudinal dyadic data has conceptually three-levels, criticism exists of using a three-level model for longitudinal dyadic data. Bolger and

[85] Random slopes for β_{1ij} and β_{2ij} are disregarded at this point. It will be tested, if it is necessary to include random slopes, by including them successively into the model and conducting a likelihood-ratio test (Wenzelburger et al., 2014).

[86] If no random effects are included into the model at upper-levels, the difference is not relevant. As mentioned before, it will be tested if it is necessary to include random slopes conducting a likelihood-ratio test.

Laurenceau (2013) appeal for the use of a two-level model instead of a three-level model with a lower within-dyad level and an upper between-dyad level.[87] They argue that usually occasions are fully crossed within dyads, as the members of the dyads are observed at the same occasions. This crossed structure leads to a within-dyad correlation between the outcomes of the two dyad members for a given occasion, which will not be modeled in a three-level model. Therefore, they suggest not to model occasions as nested within individuals but as crossed within individuals (Bolger and Laurenceau, 2013). The different structures of the data which are assumed in a three-level model with occasions at level-1, individuals at level-2 and dyads at level-3, and in a two level model with occasions at level-1 and dyads at level-2, are comparatively represented in Figure 12.

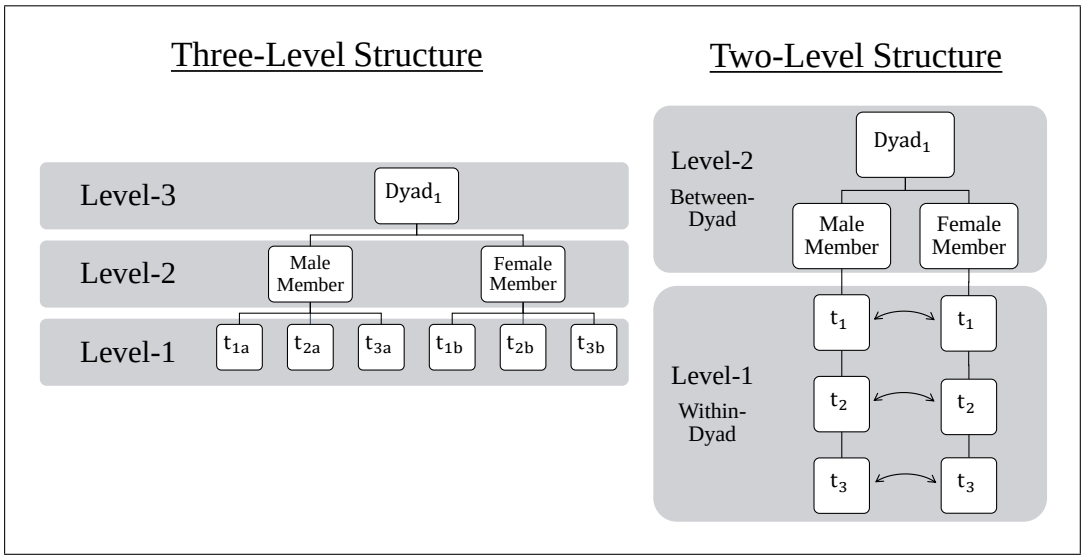

Figure 12: Three-Level Data Structure vs. Two-Level Data Structure of Longitudinal Dyadic Data.
(Source: Own presentation according to Bolger and Laurenceau (2013) and Kashy and Donnellan (2012).)

The left part of Figure 12 again displays the three-level structure of longitudinal dyadic data from Figure 11 for one dyad with distinguishable members (couples with a male and a female partner) representative for n dyads. The right part of Figure 12 now additionally displays the two-level structure with a lower, within-dyad level and an upper, between-dyad level of a dyad with distinguishable members representative for n dyads. It can be seen that in the left part of Figure 12 the different occasions are nested within individuals and individuals are nested within a dyad. No relationship between the different points in time (t) is displayed in the left part of Figure 12 and occasions,

[87] A similar discussion can also be found in an earlier paper by these authors (Laurenceau and Bolger, 2005) and is picked up later by Kenny and Kashy (2011).

individuals and dyads are represented by three different levels. Considering the right part of Figure 12, it is taken into account that the observations of the dyad members are measured at the same points in time. Hence, it is not possible to assign a given occasion to only one individual. A given occasion can always be assigned to two individuals within a dyad. Therefore, the right part of the figure displays correlations between the same points in time for different individuals. Individuals and dyads are combined to represent the between-dyad level and occasions are modeled at the lower-level, representing the within-dyad level.

Two-Level Modeling of an Over-time Standard APIM

Estimating a two-level-model from the right part of Figure 12 with a lower within-dyad level and an upper between-dyad level of the Over-time Standard APIM for job insecurity and mental health, the independent variables as well as the control variables are included at level-1. Level-1 and level-2 of a two-level model will hence look as follows (Kashy and Donnellan, 2012):[88]

Level-1 Within-Dyad:

$$\begin{aligned}\text{Mental Health}_{tij} = \beta_{0j} + \beta_{1j} JIA_{tij} + \beta_{2j} JIP_{tij} + \beta_{3j} Gender_{tij} \\ + \beta_{4j} JIA_{tij} Gender_{tij} + \beta_{5j} JIP_{tij} Gender_{tij} + \epsilon_{tj}\end{aligned} \tag{16}$$

Level-2 Between-Dyad:

$$\begin{aligned}\beta_{0j} &= \gamma_0 + \delta_0 \\ \beta_{1j} &= \chi_0 \\ \beta_{2j} &= \phi_0 \\ \beta_{3j} &= \varphi_0 \\ \beta_{4j} &= \kappa_0 \\ \beta_{5j} &= \varpi_0\end{aligned} \tag{17}$$

Equation 16 looks very similar to Equation 8 in Chapter 6.3.2. The difference to Equation 8 and hence to an APIM is the included time-index t (Kashy and Donnellan, 2012), representing the different points in time of measurement in the Over-time Standard APIM. The actor effect is presented by β_{1j} for women and by $\beta_{1j} + \beta_{4j}$ for men. The partner effect is displayed by β_{2j} for women and $\beta_{2j} + \beta_{5j}$ for men. Level-2 (Equation 17) represents the individual equations for the slopes of the variables at level-1. The slope of the intercept of level-1 is expressed by a fixed part (γ_0) and a random part (δ_0), whereas the random

[88] Control variables are not included here to improve clarity.

part varies by dyad j and hence represents the dyad-specific deviation from the fixed intercept. The slopes of the independent variables at level-1 do not vary by dyad and hence only consist of a fixed part represented by χ_0, ϕ_0, φ_0, κ_0 and ϖ_0.

Paying attention to the criticism of using a three-level model presented above and making a contribution to the methodical approach for longitudinal dyadic data, also the two-level model of Equation 16 and Equation 17 will be estimated. The estimation of the two-level model will also be performed using the Stata command *mixed*. To estimate the two-level model, two additional variables have to be generated. A dummy variable, coded 1, if an individual is female and 0 otherwise and a dummy variable, coded 1, if an individual is male and 0 otherwise (Kashy and Donnellan, 2012). These dummy variables differentiate the estimation model for women and men and enable to include separate actor and partner effects for both sexes. As considered for the three-level model, a lag 1 autoregressive covariance structure of the random effects at level-1 is also proposed for the two-level model (Kashy and Donnellan, 2012). Therefore, it is tried again to model a covariance structure, which is as similar as possible to the one which is recommended, by modeling a lag 1 autoregressive structure of the random effects of level-1 and including elapsed time.[89]

Model Comparison

In order to determine which model performs best and is therefore better suited to estimate the underlying longitudinal dyadic data, the three-level Over-time Standard APIM and the two-level Over-time Standard APIM model will be compared using the AIC, the BIC as well as the -2LL value. Additionally, a likelihood-ratio test will be conducted to determine if one of the Over-time Standard APIMs fits the data even significantly better than the other one. The comparison of the two-level and the three-level Over-time Standard APIM will demonstrate if it is necessary to model occasions as crossed, suggested by Bolger and Laurenceau (2013) and Kashy and Donnellan (2012) or if it is also possible to model them as nested. Modeling time as nested within individuals is however supported by Hoffman (2015) as long as mean differences across time are modeled using fixed effects of time.

Overview of the Estimation Strategy

Summarizing, the estimation strategy is divided into three steps. The first step contains the gradual development of a three-level model for the mental

[89] Elapsed time is not presented in Equation 16 to improve clarity.

health status (1.), which is additionally divided into two steps of development (a and b) and one step of robustness checks (c). Starting with the determination of the dependency and of the nested structure in the data (a), in the beginning a Non-Nested Model will be considered, regardless of dependency due to repeated observations or due to interpersonal relations (i.). After this, the Non-Nested Model will be expanded to a model with a two-level structure which considers dependency due to repeated observations (ii.). The resulting two-level Random-Intercept-Only Model is then expanded by an additional level leading to a model, which considers dependency due to repeated observations and due to interpersonal relations, as well as a three-level structure (iii.). In each case, a comparison of the models is carried out on the basis of the relative model fit indices, the AIC, the BIC and the -2LL value as well as the likelihood-ratio test in order to check which model performs significantly better. After a confirmation of a model with three levels, a three-level Over-time Standard APIM is established estimated subsequently, including the independent variables, the control variables and the specific error structure (b). The estimation of the three-level Over-time Standard APIM is then followed by some robustness checks, which will be immediately presented in detail before application (c). In the second step (2.), a two-level Over-time Standard APIM suggested by literature on dyadic analysis is established and estimated for job insecurity and mental health while considering the control variables and the specific error structure (a). Also after estimating the two-level Over-time Standard APIM, some robustness checks will be conducted, which will also be immediately presented in detail before application (b). After the results of the three-level Over-time Standard APIM and the two-level Over-time Standard APIM are represented separately, they will be compared in a third step (3.). To determine which model performs best, both models are compared using the the AIC, the BIC as well as the -2LL value. Additionally, a likelihood-ratio will be conducted.

1. Three-Level Modeling of an Over-time Standard APIM
    (a) Determining the Dependency and Nested Structure of the Data
        i. Estimating a Non-Nested Model
        ii. Estimating a Two-Level Random-Intercept-Only Model
        iii. Estimating a Three-Level Random-Intercept-Only Model
    (b) Estimating a Three-Level Over-time Standard APIM
    (c) Performing Robustness Checks

2. Two-Level Modeling of an Over-time Standard APIM

    (a) Estimating a Two-Level Over-time Standard APIM

    (b) Performing Robustness Checks

3. Model Comparison

7 Empirical Evidence

7.1 Descriptive Statistics

The used sample of 31,316 individual-year observations consists of 15,658 observations of men and 15,658 observations of women. This equal distribution is due to the fact that only heterosexual couples are selected for the following analysis. Over all years, 12,826 individuals and 6,376 couples are included. Thereby, not all individuals and couples are observed over the whole time period, leading to unbalanced occasions. The sample consists on average of 5,219 observations in each year. In 2002 the sample exists of 6,456 observations, in 2004 of 5,648 observations, in 2006 of 5,014 observations, in 2008 of 4,892 observations, in 2010 of 4,468 observations and in 2012 of 4,838 observations.

The sample includes individuals aged 18 up to 65, whereas the average age is about 45 years. Additionally, individuals with all possible educational backgrounds are represented as the variable measuring years in education ranges between 7 years, representing no degree and 18 years, representing an university degree for the selected sample. On average, the observed individuals spent about 13 years in education.[90] Considering the occupation of the observed individuals, the group of technicians and associate professionals are most frequently represented with 3,680 individuals followed by professionals with 3,049 individuals. The elementary occupation group is the least represented occupation group with 1,000 individuals. 1,220 individuals belong to the occupation group of legislators, senior officials and managers. The occupation group of clerks is represented by 1,905 individuals. 1,646 individuals work as service workers, shop sales workers or market sales workers. Finally, 1952 individuals however belong to the occupation group of skilled agricultural workers, fishery workers, craft and related trade workers.

Job Insecurity

Considering the distribution of job insecurity over the individual years, job insecurity is most of all represented in 2004. In this year, about 60.43% of the observed individuals report to be very concerned or somewhat concerned about their job security. In the other years, the proportion of individuals reporting job insecurity ranges between about 50.94% and about 57.08% and is least with about 44.67% in 2012. Over all years, job insecurity can be observed in 16,574 cases. This represents that concerns about job security occur in more

[90] Table 29 in the Appendix displays the summary statistics of the used variables representing mean, standard deviation, the minimum value and the maximum value.

than half of the observed cases and are hence widespread in the used sample of couples living in Germany between 2002 and 2012. Of the 16,574 observations, 7,955 observations go back to women reporting job insecurity and 8,619 observations go back to men reporting job insecurity. In the present sample, job insecurity is hence more popular among male individuals. Additionally, the measurement of job insecurity can be distinguished between the categories of being very concerned about job security and of being somewhat concerned about job security. Figure 13 represents the distribution of job insecurity by gender pooled over all observed years and divided into the categories being very concerned about job security, being somewhat concerned about job security, and being not concerned about job security.

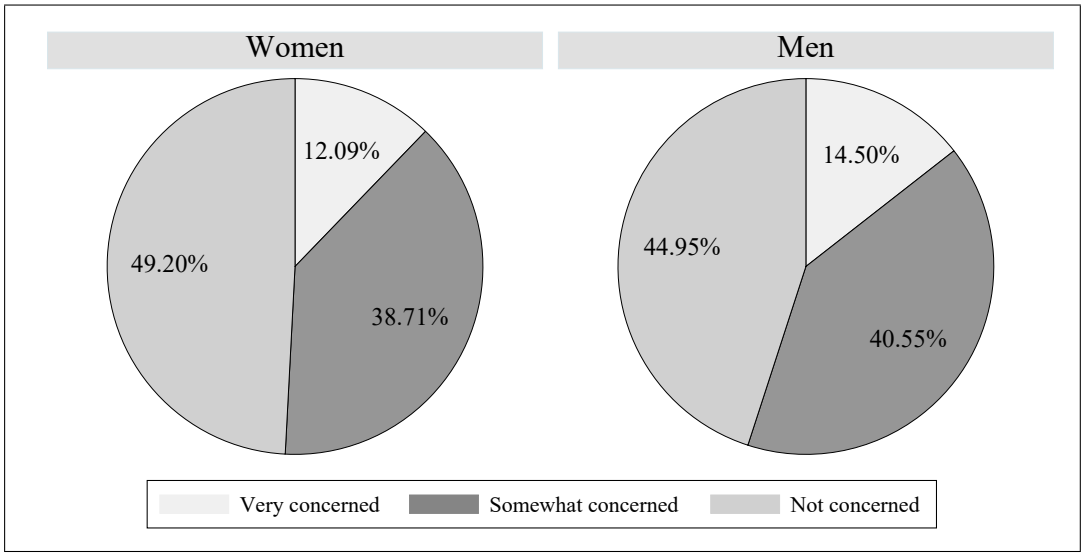

Figure 13: Job Insecurity by Gender.
(Source: Own presentation.)

Women report 1,893 times that they are very concerned about their job security, which corresponds to about 12.09% of all individual-year observations of women. Furthermore, women report 6,062 times that they are somewhat concerned about their job security over all observed years (about 38.72%). The remaining 49.20% of all individual-year observations of women go back to the category of being not concerned about job security. For men (right part of Figure 13), the category somewhat concerned is much more often reported by men with 6,349 cases, which corresponds to about 40.55%, than the category very concerned with 2,270 cases, which equals about 14.50% of all individual-year observations of men. The remaining 44.95% of all individual-year observations of men therefore represent the category of being not concerned about job security. Pooled over gender and all observed years, in about 47.07% of the cases no job insecurity is present, in about 39.63% of the cases, individuals are

somewhat concerned about their job security and in about 13.29% of all cases, individuals are even very concerned about their job security.

Figure 14 displays that the existence of job insecurity in different age groups is especially in the younger age groups quite similarly distributed. Considering individuals under 30 years, about 55.96% report job insecurity. Of the individuals aged 30 to 39 as well as for the age group 40 to 49 the proportion of individuals suffering from job insecurity amounts to about 56.49%. However, regarding individuals aged 50 years and older, a slightly lower proportion of individuals who report job insecurity is found. About 45.82% of the individuals aged 50 or older report to experience job insecurity.

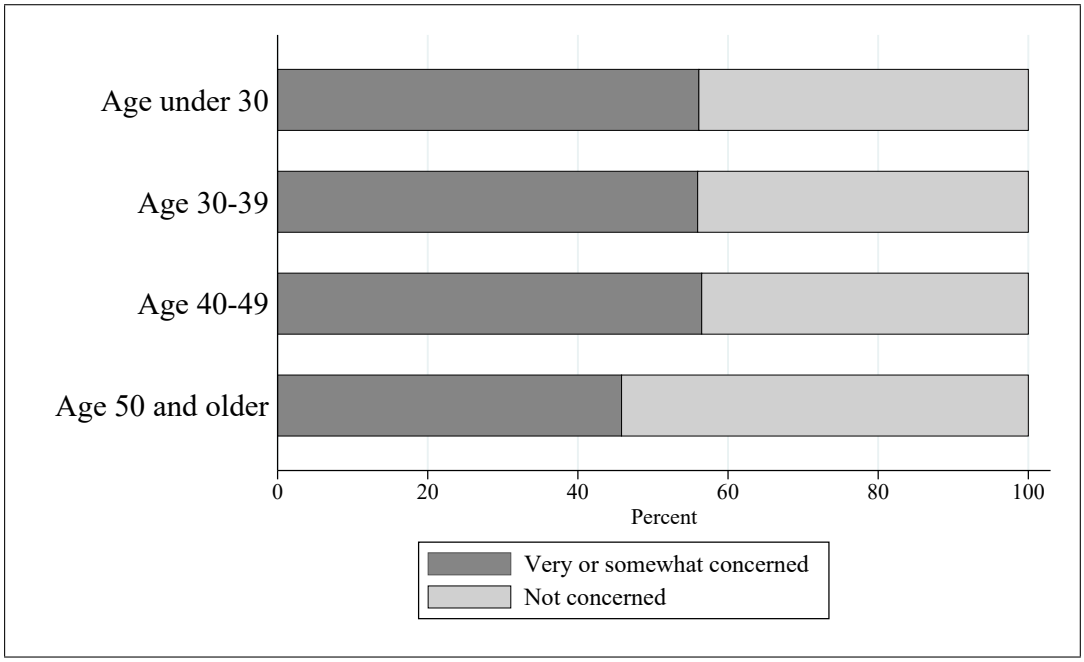

Figure 14: Job Insecurity by Age.
(Source: Own presentation.)

Considering education, it could be found that job insecurity is most common among individuals with no degree or a lower school degree, displayed in Figure 15. About 64.29% of the individuals, who are spending only between 7 and 9 years in education, report to suffer from job insecurity. Among individuals with an intermediary school degree or professional college degree about 57.74% report to be very or somewhat concerned about their job security. About 49.07% of the individuals with at least a high school degree report to suffer from job insecurity. Individuals, who spent 18 years in education and are holding a university degree, are less affected by job insecurity. Among those, only about 36.86% report to suffer from job insecurity. Summarizing, rising years of education and therefore, higher educational degrees are in line with lower experiences of job insecurity.

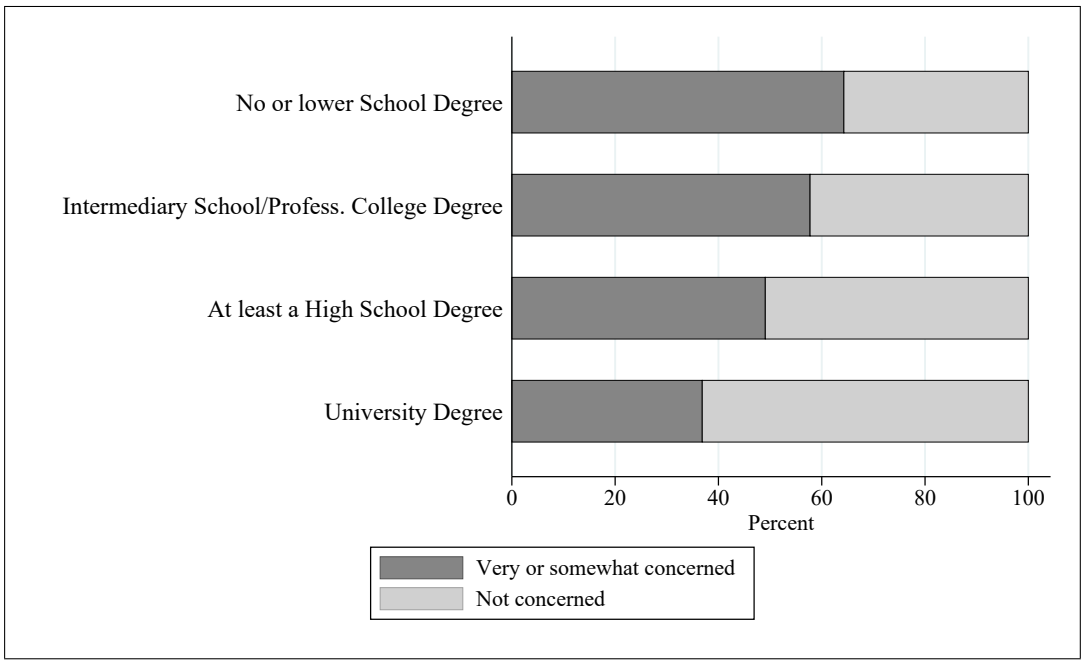

Figure 15: Job Insecurity by Education.
(Source: Own presentation.)

Figure 16 represents the distribution of job insecurity by the different occupation groups based on the ISCO. Firstly, it can be seen that job insecurity is represented in all occupations controlled for. The largest proportion of reported job insecurity is found among plant operators, machine operators and assemblers. In this occupation group, 70.97% of the individuals report job insecurity pooled of all observed years. Those individuals are closely followed by individuals in the occupation group of craft and related trade workers with a proportion of 69.05% of reported job insecurity and skilled agricultural and fishery workers with a proportion of 64.91% of reported job insecurity. Individuals in occupations which are belonging to the second occupation group, summarized by professionals, represent the lowest proportion of reported job insecurity with about 37.81%. All other occupations represent proportions between 50.22% and 59.00%. Legislators, senior officials and managers are displayed with a proportion of 50.22% of reported job insecurity. 51.16% of all individual-year observations of the occupation group of technicians and associate professionals go back to individuals, reporting job insecurity. Considering service workers, shop sales workers and market sales workers, 53.37% of all individual-year observations of this occupation group present job insecurity. In the occupation group of clerks 55.03% declare to experience job insecurity over the observed years. Finally, in the occupation group of elementary occupations, 59% of the individuals report job insecurity pooled of all observed years. The hierarchical order of the occupation groups is therefore not displayed in the proportions of experienced job insecurity in the different

groups. However, a tendency to higher proportions of reported job insecurity in less complex occupations can be derived from Figure 16 with exception of the occupation group of elementary occupations.

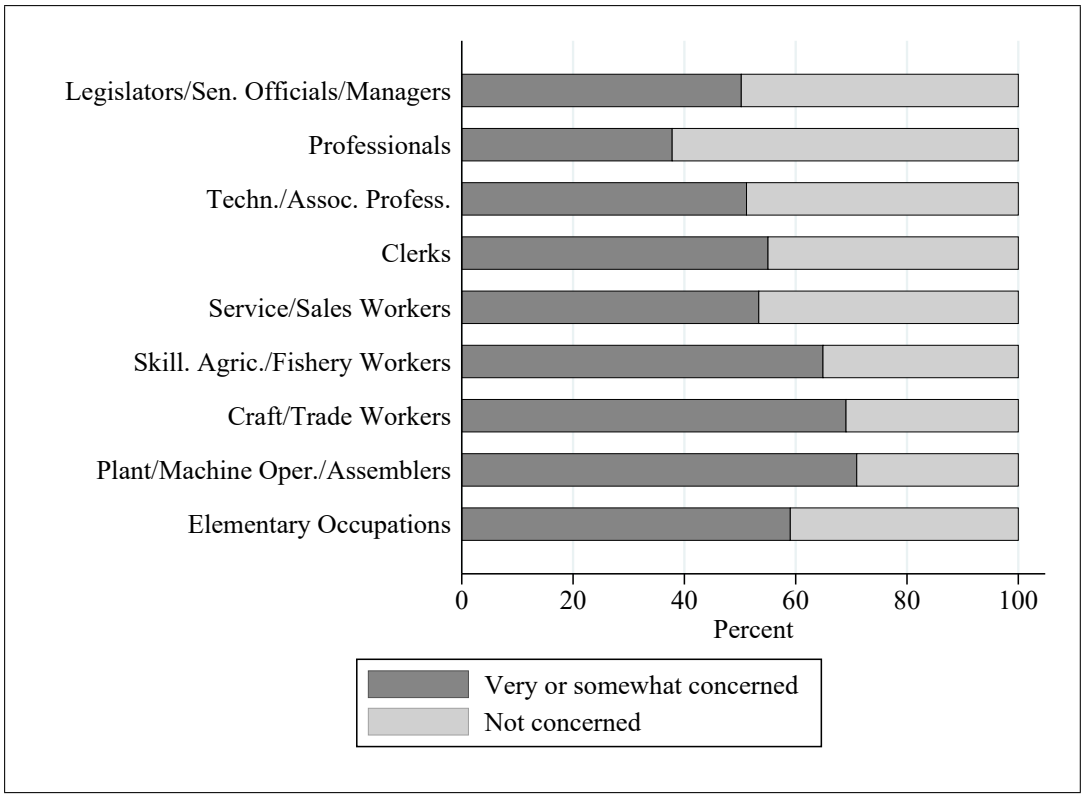

Figure 16: Job Insecurity by Occupation
(Source: Own presentation.)

In summary, in over half of the observed cases of all individuals and years, job insecurity in terms of being somewhat or even very concerned about job security is reported. Thereby, men, younger individuals, plant operators, machine operators, assemblers, craft and related trade workers report most commonly to suffer from job insecurity. Additionally, the proportion of reported job insecurity decreases with rising years of education.

Mental Health

Table 2 represents the mean and the standard deviation (SD) for the mental health status as well as the number of observations (N) for the total sample and for the subsamples of female and male individuals. The mean and standard deviation of the mental health amount to 50 respectively 10 in the total sample, which is used as reference for the interpretation of the values of the subsamples of women and men. Differences in the mental health status among gender amount to about 1.80 points, which represents about 18.00% of a standard deviation, as the mental health score is normed to have a standard deviation

of 10. Men on average represent a better mental health status than women. The average mental health status for men is about 0.91 points above the total average. For women however, the average mental health status is about 0.91 points lower than the total average score of the mental health status.

Table 2: Descriptive Statistics of the Mental Health Status across Gender

	Mean	**SD**	**N**
Total	50.00	10.00	31,316
Gender			
Males	50.91	09.60	15,658
Females	49.09	10.31	15,658

Note: Means and standard deviations are rounded to two decimal places.

Considering different age groups of the sample, Table 3 represents the mean and the standard deviation (SD) of the mental health status and the number of observations (N) for the subsamples of individuals under the age of 30, individuals aged between 30 and 39, individuals aged between 40 and 49 as well as the subsample of individuals above the age of 50. It can be seen that the mental health status is on average worse for younger individuals than for older individuals. The mean value for individuals aged under 30 for example amounts to about 48.63, whereas the mean value for individuals aged 50 or older, amounts to about 51.10. This in total leads to a mental health status for young women, which is about 1.92 points (about 19.20% of a standard deviation) under the average score of mental health of the whole sample.[91]

Table 3: Descriptive Statistics of the Mental Health Status across Age

	Mean	**SD**	**N**
Total	50.00	10.00	31,316
Age Groups			
Aged under 30	48.63	10.12	1,816
Aged 30-39	49.07	10.00	7,211
Aged 40-49	49.84	09.87	12,249
Aged 50 and older	51.10	10.02	10,040

Note: Means and standard deviations are rounded to two decimal places.

Regarding education, Table 4 considers the subsample of individuals with no or a lower school degree, the subsample of individuals with an intermediary

[91] For female individuals aged under 30, the mean value amounts to about 48.08 points.

school or professional college degree, the subsample of individuals with at least a high school degree and finally the subsample of individuals with a university degree. Table 4 again represents the mean and the standard deviation (SD) of the mental health status as well as the number of observations (N) for these subsamples. It is presented, that the mental health status ranges from 49.72 points for individuals with no degree or a lower school degree over 49.73 points for individuals with at least a high school degree and 49.99 points for individuals with an intermediary school or professional college degree up to 50.52 points for individuals with a university degree. Hence, there are very similar average mental health scores for individuals with no degree or a lower school degree and individuals with at least a high school degree. Both groups' averages lay under the sample average of the mental health score with about 0.28 points (about 2.80% of a standard deviation) and about 0.27 points (about 2.70% of a standard deviation). Individuals with an intermediary school or professional college degree are also under, but very close to the sample average mental health score with a distance of 0.01 points (about 0.10% of a standard deviation). However, individuals with a university degree on average display a mental health score above the sample average score by about 0.52 points, which represents about 5.20% of a standard deviation. Nevertheless, each education group average score is near the sample average score of 50 points.

Table 4: Descriptive Statistics of the Mental Health Status across Education

	Mean	**SD**	**N**
Total	50.00	10.00	31,316
Education Groups			
No or lower School Degree	49.72	10.21	1,610
Intermediary School/Professional College Degree	49.99	10.01	17,846
At least a High School Degree	49.73	10.06	7,072
University Degree	50.52	09.80	4,788

Note: Means and standard deviations are rounded to two decimal places.

Table 5 displays the mean and the standard deviation (SD) of the mental health status and the number of observations (N) for the subsamples of the different occupation groups. It can be seen, that the average mental health score among occupations ranges between 49.01 for clerks and 50.84 for legislators, senior officials and managers. Hence, the hierarchical order of the occupation groups is not represented in the average mental health scores. Although, it can be seen that the first group has an average mental health score of about 0.84 points, which is about 8.40% of a standard deviation above the sample average

score, the elementary occupation group does not have the worst average score with about 49.87. The eighth group, consisting of plant operators, machine operators and assemblers, has even an average mental health score of about 50.80 points, which is about 0.80 points (about 8% of a standard deviation) above the sample average score of the mental health status. Hence, individuals who belong to the eighth occupation group on average display a better mental health status than the sample average score. The worst average mental health status is displayed by the occupation group of clerks with 49.01 points, followed by the one of technicians and associate professionals with 49.56 points.

Table 5: Descriptive Statistics of the Mental Health Status across Occupations

	Mean	**SD**	**N**
Total	50.00	10.00	31,316
Occupations			
Legislators/Sen. Officials/Managers	50.84	09.90	2,228
Professionals	50.23	09.88	6,671
Techn./Assoc. Profess.	49.56	10.30	7,533
Clerks	49.01	10.21	3,669
Service/Sales Workers	50.17	09.98	3,232
Skill. Agric./Fishery Workers	50.44	09.57	322
Craft/Trade Workers	50.41	09.60	3,738
Plant/Machine Oper./Assemblers	50.80	09.47	1,919
Elementary Occupations	49.87	10.09	2,004

Note: Means and standard deviations are rounded to two decimal places.

Summarizing, a mental health status above the average mental health status is displayed by men and older individuals, legislators, senior officials, managers, plant operators, machine operators and assemblers. The educational background however does not play a very important decisive role for the mental health status considering descriptive statistics.

Correlation Analysis

Table 6 represents the correlation matrix of the variables, which are used in the following analysis, including the dependent variable, the independent variables and the control variables. In order to interpret the values in Table 6, it is oriented towards the classification recommended by Cohen (1988) and Cohen et al. (2003). Following Cohen (1988) and Cohen et al. (2003), values smaller

than ±0.30 are considered as small. Values grater than ±0.30 and smaller than ±0.50 are classified as moderate and values greater or equal than ±0.5 are considered as large.[92]

Looking at the correlation coefficients in Table 6, it can be seen that the mental health status is significantly related to the independent variables job insecurity, partner's job insecurity and gender. The correlation coefficient of the mental health status and own job insecurity amounts to -0.163. The correlation between the mental health status and partner's job insecurity however is displayed with -0.099. To categorize these correlations, the classification by Cohen et al. (2003) can be considered. Following Cohen et al. (2003), the correlation between the mental health status and own job insecurity can be classified as small. The correlation between the mental health status and partner's job insecurity is however located at the border between minor and small. Nevertheless, both correlations are significant and negative as assumed. The correlation between the mental health status and own job insecurity is however more than 1.5 times stronger than the correlation between the mental health status and partner's job insecurity.

The correlation coefficients between the mental health status and gender as well as the one between the mental health status and age, display similar values in terms of strength as the correlation between the mental health status and partner's job insecurity with 0.091 and 0.092. The correlation coefficients are also significant at the 1%-level, but can be classified as minor correlations, because of their strength. Regardless of their classification as minor correlations, the results are in line with the summary statistics presented above, as both correlation coefficients display significant positive signs.

The years an individual spends in education are also significantly positively related to the mental health status at the 5%-level of significance. The strength of the correlation coefficient is however negligible. To represent correlations in general, occupation is included as a continuous variable with higher values meaning less complexity in Table 6. The correlation coefficient between the mental health status and occupation is however not significant. Considering the individual occupation dummy variables, significant correlations exist. Table 30 in the Appendix displays the correlation coefficients for the individual occupation dummy variables. A significant correlation between the mental health status and all occupation groups can be found, except for the group of service workers, shop sales workers and market sales workers as well as the

[92] This classification will be used in the following to classify the correlation coefficients in Table 6 as well as those in Table 30.

elementary occupation group. However, all correlations are below a correlation of 0.1 and can hence be classified as minor, following Cohen et al. (2003). The correlation between occupation based on the ISCO and the years an individual spends in education displays the highest significant correlation in Table 6 with -0.541. A higher ISCO88 Code and hence a less complex job is related to less years in education. This large correlation has to be taken into consideration in the analysis regarding multicollinearity, while including both variables into one estimation model.

Table 6: Correlation Matrix of Explanatory Variables

	1	2	3	4	5	6	7
1. Mental Health Status	1.000						
2. Job Insecurity	-0.163***	1.000					
3. Job Insecurity Partner	-0.099***	0.313***	1.000				
4. Gender	0.091***	0.042***	-0.042***	1.000			
5. Age	0.092***	-0.095***	-0.094***	0.138***	1.000		
6. Yrs in Education	0.013**	-0.160***	-0.151***	0.030***	0.068***	1.000	
7. ISCO88Code	0.006	0.170***	0.142***	0.100***	-0.069***	-0.541***	1.000

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Correlations are rounded to three decimal places. Occupation is included as continuous variable for clearer presentation of the results. A correlation matrix with the occupation dummy variables can be found in Table 30 in the Appendix.

7.2 Over-time Standard APIM

7.2.1 Three-Level Modeling

7.2.1.1 Development

Before presenting the results of the three-level Over-time Standard APIM with occasions at level-1, individuals at level-2 and dyads at level-3, the model has to be developed gradually. The results of each step of this development are represented in the following. In the first step, the dependency due to repeated observations is determined. This is done by estimating a Non-Nested Model for the dependent variable represented by the mental health status. In addition, the results of this Non-Nested Model are compared to those of a two-level Random-Intercept-Only Model with occasions at level-1 and individuals at level-2. In the second step, the dependency due to interpersonal relations is additionally considered. Therefore, the two-level Random-Intercept-Only Model is compared with a three-level Random-Intercept-Only Model for the mental health status that models occasions at level-1, individuals at level-2 and dyads at level-3. In each step, the corresponding ICC is represented. Furthermore, the relative model fit indices the AIC, the BIC and the -2LL value are used to compare the different model fits. Significant differences concerning model fit are determined using a likelihood-ratio test, which tests the null hypothesis that the less complex model fits the underlying data significantly better than the more complex one under the condition that one of the models is an extent of the other model that should be compared.

Non-Nested Model

The Non-Nested Model corresponds to a standard Linear Regression Model without independent and control variables. The estimation results of the Non-Nested Model for the dependent variable, the mental health status, are represented in Table 7. Due to the fact that no independent or control variables are included, the coefficient of the constant displays the mean of the mental health status over all 31,316 observations. Since the mental health status is set to have a mean of 50 and a standard deviation of 10, the average mental health status is also estimated with 50. In addition, the AIC and the BIC values as well as the -2LL value are represented in the lower part of Table 7. The AIC value amounts to 233,089.5, the BIC value to 233,106.2 and finally the -2LL value amounts to 233,085.4. However, these indices for relative model fit do not become relevant until comparing the Non-Nested Model with other models.

Table 7: Non-Nested Model – Linear Regression

	Linear Regression
Constant	50.0000***
	(0.0565)
AIC	233089.5
BIC	233106.2
-2 Log likelihood	233085.4
Number of Observations	31,316

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Dependent variable: MCS. Estimation procedure: ML.

Two-Level Random-Intercept-Only Model

While including an additional level to the Non-Nested Model presented in Table 7, a two-level Random-Intercept-Only Model results. In the two-level Random-Intercept-Only Model, dependency due to repeated observations is considered and hence occasions are modeled to be nested within individuals. Table 8 shows the estimation results of such a two-level Random-Intercept-Only Model for the mental health status as dependent variable and with occasions at level-1 and individuals at level-2. Compared to the Non-Nested Model in Table 7, it can be seen that next to the number of observations, now also the number of individuals is represented. The number of individuals is displayed with 12,732 individuals. The number of observations remains the same with 31,316 observations pooled over the years 2002 to 2012. The coefficient of the constant and hence the average effect across individuals still displays a value close to 50, because the mental health status is set to have a mean of 50.

Furthermore, differently to the Non-Nested Model, the results of the two-level Random-Intercept-Only Model additionally represent the proportion of variance in the dependent variable, which is due to the variance at level-1 and the proportion of variance, which is due to the variance at level-2. The level-1 variance is estimated with 52.4470 and the level-2 variance with 48.4553. This displays, that about 52% $(52.4470/(48.4553+52.4470)*100)$ of the variance in the mental health status is due to differences between occasions within individuals and about 48% $(48.4553/(48.4553+52.4470)*100)$ of the total variance in the mental health status is due to differences between individuals. Since the model is a two-level Random-Intercept-Only Model, the calculation of the ICC is the same as for the proportion of variance of the level-1 variance with

$48.4553/(48.4553 + 52.4470) = 0.4802$.[93] In a two-level Random-Intercept-Only Model it applies, that the higher the ICC, the more stable is the mental health status over the individual occasions.

Table 8: Two-Level Random-Intercept-Only Model

	Two-Level
Constant	49.9149***
	(0.0776)
Level 2 Variance	48.4553***
	(0.4914)
Level 1 Variance	52.4470***
	(0.2693)
AIC	226728.6
BIC	226753.7
-2 Log likelihood	226722.6
Number of Observations	31,316
Number of Individuals	12,732

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Dependent variable: MCS. Estimation procedure: ML.

Nevertheless, the proportion of variance, which is due to repeated observations, amounts with 52% to more than half of the total variance in the mental health status. This indicates that it is useful to model occasions and individuals at different levels. This is in line with previous literature, recommending the use of a multilevel model instead of a model with no different levels from an ICC greater than 0.10, respectively greater than 10% (Lee, 2000; Killip et al., 2004). Therefore, modeling occasions at level-1 and individuals at level-2 and hence occasions nested within individuals, is supported using the underlying data.

Looking at the relative model fit indices, the two-level Random-Intercept-Only Model displays an AIC value of 226,728.6 and a BIC value of 226,753.7. Furthermore, the -2LL amounts to 226,722.6. Therefore, the relative model fit indices display lower values for the two-level Random-Intercept-Only Model than for the Non-Nested Model. This indicates a better model fit of the two-level Random-Intercept-Only Model than of the Non-Nested Model presented in Table 7. The result of a likelihood-ratio test of both models is represented

[93] In the following, the ICC is calculated by the ratio between the variance within a level and the total variance. This kind of calculation is represented in connection with MLM by Becker and Lois (2015). The estimation of the ICC recommended by Kenny et al. (2006) for negative non-independence is not used, because no negative non-independence is considered.

in Table 9. The likelihood-ratio test verifies the null hypothesis $H0$ that the Non-Nested Model fits the data significantly better than the two-level Random-Intercept-Only Model, because the Random-Intercept-Only Model is an extent of the Non-Nested Model. The results display, that the null hypothesis $H0$ can be rejected. Therefore, it can be concluded, that the two-level Random-Intercept-Only Model fits the underlying data even significantly better than the Non-Nested Model. Occasions should be modeled as nested within individuals, using the underlying data.

Table 9: Likelihood-Ratio Test – Non-Nested Model vs. Two-Level Random-Intercept-Only Model

Likelihood-Ratio Test	LR chi2(1) = 6362.82
(Assumption: Non-Nested in 2-Level Model)	Prob>chi2 = 0.0000

Three-Level Random-Intercept-Only Model

In a next step, the dependency due to repeated observations as well as the dependency due to interpersonal relations are considered simultaneously. This results in a three-level Random-Intercept-Only Model. The three-level Random-Intercept-Only Model includes occasions at level-1, individuals at level-2 and dyads at level-3. Hence, in such a model it is assumed that occasions are nested within individuals and individuals are nested within dyads. The results of the three-level Random-Intercept-Only Model are represented in Table 10. Next to the number of observations and the number of individuals, now also the number of dyads is displayed. The used data consists of 6,376 different dyads with 12,826 different individuals, leading to 31,316 individual-year observations between 2002 and 2012. In the three-level Random-Intercept-Only Model, the constant displays the average effect across individuals within dyads. The coefficient of the constant is again close to 50 as it amounts to about 49.8926.

The total variance in a three-level Random-Intercept-Only Model is divided in the variances at the three different levels. The variance amounts to 52.2015 at level-1, to 21.5140 at level-2 and to 27.6222 at level-3. This means that 52% $(52.2015/(27.6222 + 21.5140 + 52.2015) * 100)$ of the total variance is represented by between-dyads variance, 21% $(21.5140/(27.6222 + 21.5140 + 52.2015) * 100)$ of the total variance goes back to variance between individuals within dyads and that the remaining 27% $(27.6222/(27.6222 + 21.5140 + 52.2015) * 100)$ of the total variance is represented by variance between occasions within individuals. The ICC for occasions within individuals and dyads (ICC_{OwIwD}) is calculated by $(27.6222 + 21.5140)/(27.6222 + 21.5140 +$

52.2015) and amounts to 0.4849 which corresponds to about 48%. The ICC for individuals within dyads (ICC_{IwD}) however is calculated by $27.6222/(27.6222+21.5140) = 0.5622$ and hence amounts to about 56%. Both ICC values are above 0.10 respectively 10%, which supports to model the data with three-levels, where occasions are assumed to be nested within individuals and individuals are assumed to be nested within dyads (Lee, 2000; Killip et al., 2004).

Table 10: Three-Level Random-Intercept-Only Model

	Three-Level
Constant	49.8926***
	(0.0911)
Level 3 Variance	27.6222***
	(0.5086)
Level 2 Variance	21.5140***
	(0.4129)
Level 1 Variance	52.2015***
	(0.2666)
AIC	225829.3
BIC	225862.7
-2 Log likelihood	225821.2
Number of Observations	31,316
Number of Individuals	12,826
Number of Dyads	6,376

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Dependent variable: MCS. Estimation procedure: ML.

Regarding the relative model fit indices, the estimation results of the three-level Random-Intercept-Only Model display that the AIC value amounts to 225,829.3, the BIC value to 225,862.7 and the -2LL value to 225,821.2. Comparing the relative model fit indices of the three-level Random-Intercept-Only Model with those of the two-level Random-Intercept-Only Model, it can be seen that the AIC and the BIC values as well as the -2LL value for the three-level Random-Intercept-Only Model are smaller than the values for the two-level Random-Intercept-Only Model. This indicates that the three-level Random-Intercept-Only Model fits the underlying data more accurate than the Random-Intercept-Only Model with two-levels. In line with this, the null hypothesis of the likelihood-ratio test H_0, considering that the two-level Random-Intercept-Only Model fits the data significantly better than the three-level Random-Intercept-Only Model, can be rejected. The result of the likelihood-

ratio test is presented in Table 11. The three-level Random-Intercept-Only Model fits the data significantly better than the two-level Random-Intercept-Only Model. This implies that modeling occasions nested within individuals and individuals nested within dyads fits the data significantly better than modeling occasions nested within individuals. Dependency due to repeated observations as well as the dependency due to interpersonal relations are existent and have to be considered simultaneously, while using the present longitudinal dyadic data.

Table 11: Likelihood-Ratio Test – Two-Level vs. Three-Level Random-Intercept-Only Model

Likelihood-Ratio Test	LR chi2(1) = 901.37
(Assumption: 2-Level nested in 3-Level Model)	Prob>chi2 = 0.0000

7.2.1.2 Empirical Results

After presenting that dependency due to repeated observations and dependency due to interpersonal relations exist in the used data, a three-level Over-time Standard APIM with occasions at level-1, individuals at level-2 and dyads at level-3 is estimated to verify the proposed hypotheses about spillover and crossover of job insecurity to the mental health status. Thereby, occasions are assumed to be nested within individuals and individuals in turn are assumed to be nested within dyads. The results of the three-level Over-time Standard APIM are presented in Table 12. The first column displays the results of the three-level Over-time Standard APIM including only the independent variables job insecurity, partner's job insecurity and gender as well as the corresponding interaction terms (Job Insecurity#Gender and Job Insecurity Partner#Gender) and the variable measuring time ($Time$). Hereinafter, this model will be referred to as three-level Base APIM. The second column however displays the results, when the control variables age, education and the occupation dummy variables based on the ISCO are additionally included into the model. In the following, this model will be referred to as three-level Full APIM.

Table 12: Three-Level Over-time Standard APIM

	Three-Level	
	(1)	(2)
	Base APIM	Full APIM
Constant	50.2517***	50.9166***
	(0.1844)	(0.3027)
Gender	2.0668***	1.8226***
	(0.1784)	(0.1866)
Job Insecurity	-1.9231***	-1.8758***
	(0.1587)	(0.1589)
Job Insecurity Partner	-0.6518***	-0.6379***
	(0.1624)	(0.1625)
Job Insec.#Gender	-0.4657**	-0.4988**
	(0.2285)	(0.2288)
Job Insec. Partner#Gender	0.2502	0.2549
	(0.2285)	(0.2285)
Time	0.0019	-0.0999***
	(0.0306)	(0.0326)
Age		0.0783***
		(0.0087)
Yrs in Education		0.0491
		(0.0343)
Legislators/Senior Officials/Managers		-0.0935
		(0.3341)
Professionals		-0.6157**
		(0.3115)
Techn./Assoc. Profess.		-0.2283
		(0.2720)
Clerks		-0.5309*
		(0.2946)
Service/Sales Workers		0.3363
		(0.2999)
Agric./Fishery/Craft/Trade Workers		0.0550
		(0.2903)
Plant/Machine Operators/Assemblers		0.4110
		(0.3317)

Table 12 (continued): Three-Level Over-time Standard APIM

Level 3 Variance	26.3250***	25.7156***
	(0.4852)	(0.4795)
Level 2 Variance	15.0133***	14.8617***
	(0.4436)	(0.4432)
Level 1 Variance	56.3503***	56.3997***
	(0.3721)	(0.3730)
F(JI;JI#Gender)	367.74***	352.51***
F(PJI;PJI#Gender)	22.78***	21.38***
AIC	225035.5	224955.3
BIC	225127.4	225122.4
-2 Log likelihood	225013.6	224915.4
Number of Observations	31,316	31,316
Number of Individuals	12,826	12,826
Number of Dyads	6,376	6,376

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Dependent variable: MCS. Estimation procedure: ML. Base category for Gender: Men. Base category for occupation dummy variables: Elementary occupations.

Three-Level Base APIM

(a) Spillover Hypotheses

Starting with column 1 and considering hypothesis $H1a$, and hence the negative spillover of job insecurity for women (gender = 0), the results of the three-level Base APIM show that the variable measuring job insecurity is significantly negative related to the mental health status (women's actor effect). Women who suffer from job insecurity, on average display a worse mental health status than women who do not suffer from job insecurity. The effect size of women's actor effect displays that suffering from job insecurity decreases the mental health status of women on average by about 1.92 points, which corresponds to a decrease by about 19.20% of a standard deviation of the mental health status. Thereby, women's actor effect is displayed to be significant at the 1%-level of significance and the results confirm the negative spillover hypothesis for women.

Considering hypothesis $H1b$ and hence the negative spillover of job insecurity for men, the actor effect of men (gender = 1) is displayed by the sum of the coefficient of job insecurity and the interaction term of job insecurity and gender (Job Insec.#Gender). The results display that men who suffer from

job insecurity have on average a decreased mental health status by about 2.39 points $(-1.9231 + (-0.4657))$. This corresponds to a decrease of the mental health status of about 23.90% of a standard deviation of the mental health status. The significance of men's actor effect is determined using an F-Test of joint significance for the coefficient of the variable measuring job insecurity and the coefficient of the corresponding interaction term with gender (Job Insecurity#Gender). The result of the F-Test is presented in the lower part of Table 12 (F(JI;JI#Gender)) and displays a significance of male's actor effect at the 1%-level of significance. Hence, the mental health status of a man who suffers from job insecurity is significantly worse than the mental health status of a man who does not suffer from job insecurity. Comprehensively, $H1b$ and hence the spillover of job insecurity to the mental health status for men can be confirmed, considering the present longitudinal dyadic data.

In hypothesis $H1c$ it is assumed that the mental health status of a man who suffers from job insecurity is worse than the mental health status of a woman, who suffers from job insecurity. Concerning this, the negative relationship between job insecurity and mental health is displayed to be higher for men than for women by about 0.47 points. Hypothesis $H1c$ regarding the different vulnerability of job insecurity for women and men is confirmed by the estimation results of the three-level Base APIM.

(b) Crossover Hypotheses

The negative crossover hypothesis $H2a$, assuming the crossover effect from men's job insecurity to women's mental health status (men's partner effect), is considered in the following. The effect is represented in Table 12 by the dummy variable measuring job insecurity of the partner (Job Insec. Partner). If a woman is in a relationship with a man who suffers from job insecurity, the mental health status of this woman is decreased on average by about 0.65 points, corresponding to about 6.50% of a standard deviation decrease in the mental health status. Thereby, the estimation result of this variable displays a significant negative effect at the 1%-level of significance and hence confirms the negative crossover hypothesis of men's job insecurity on women's mental health status.

Regarding hypothesis $H2b$ and hence the negative crossover of women's job insecurity to men's mental health status (women's partner effect), the sum of the coefficients of the dummy variable measuring job insecurity of the partner and the corresponding interaction term with gender (Job Insec. Partner#Gender) has to be considered. If a man is in a relationship with a woman who suffers from job insecurity, the mental health status is on average decreased by

about 0.40 points ($-0.6518 + 0.2502$), which represents a decrease of 4.00% of a standard deviation of the mental health status. Thereby, the joint significance of partner's job insecurity and the interaction term between partner's job insecurity and gender (Job Insec. Partner#Gender) are tested using an F-Test. The result of this F-Test is presented in the lower part of Table 12 (F(PJI;PJI#Gender)). It displays that the negative partner effect from men to women is significant at the 1%-level of significance. Hypothesis $H2b$ can additionally be confirmed and both hypotheses regarding negative crossover for women and men are validated by the three-level Base APIM.

To examine the different vulnerability for women and men with regard to crossover of job insecurity and hence hypothesis $H2c$, the effect sizes of women's and men's partner effects are compared. Men's partner effect displays a higher effect size than women's partner effect by about 0.25 points. Hence, the crossover hypothesis $H2c$, regarding a worse mental health status of women in a relationship with men who suffer from job insecurity than of men who are in a relationship with women who suffer from job insecurity, is confirmed. The results of the three-level Base APIM with independent variables not only confirm the negative crossover hypotheses for women and men, but also the different vulnerability of job insecurity across gender to the disadvantage of men.

(c) Further Results

Another result represented in column 1 shows, that being men (gender = 1) is on average related to an increased mental health status by about 2.07 points, which corresponds to an increase of about 20.70% of a standard deviation of the mental health status. This gender effect is significant at the 1%-level of significance. The variable time, which is included into the model to capture time trends, is however not significantly related to the mental health status.

(d) Distribution of Variance and Goodness of Fit

Looking at the lower part of Table 12, it can be seen that the variance due to differences between individuals amounts to about 58% $((56.3503/(26.3250 + 15.0133 + 56.3503)) * 100)$ of the total variance. The variance due to differences within dyads amounts to about 15% $((15.0133/(26.3250 + 15.0133 + 56.3503)) * 100)$. Finally, about 27% $((26.3250/(26.3250 + 15.0133 + 56.3503)) * 100)$ of the total variance arises due to differences between dyads. This leads to an ICC for occasions within individuals and dyads (ICC_{OwIwD}) of about 0.42 $((26.3250 + 15.0133)/(26.3250 + 15.0133 + 56.3503))$, respectively 42% and an ICC for individuals within dyads (ICC_{IwD}) of about 0.64 $(26.3250/(26.3250 +$

15.0133)), respectively 64%. The results of the ICCs indicate that it is useful to model the present data with three-levels, where occasions are nested within individuals and individuals are nested within dyads. Regarding the relative model fit indices, it can be seen that the AIC value of the three-level Base APIM amounts to 225,035.5, the BIC value amounts to 225,127.4 and finally, the -2LL value amounts to 225,013.6. Comparing these relative model fit indices of the three-level Base APIM with the indices of the three-level Random-Intercept-Only Model without independent variables, all three relative model fit indices display lower values and hence a better model fit for the three-level Base APIM with independent variables. The result of a likelihood-ratio test, including the three-level Random-Intercept-Only Model and the three-level Base APIM, is presented in Table 13. The result shows that the three-level Base APIM fits the data significantly better than the model without independent variables as the null hypothesis $H0$ is rejected.

Table 13: Likelihood-Ratio Test – Three-Level Random-Intercept-Only Model vs. Base APIM

Likelihood-Ratio Test	LR chi2(7) = 807.77
(Assumption: Intercept Only nested in Base APIM)	Prob>chi2 = 0.0000

Three-Level Full APIM

Column 2 of Table 12 presents the results of the three-level Full APIM where it is controlled for age, education and the occupation dummy variables based on the ISCO. However, before the control variables are included into the model, it has to be checked for multicollinearity, as a significant large correlation between occupation and the years an individual spends in education is identified in the correlation analysis represented in Table 6 in Chapter 7.1. To comply with this, a Variance Inflation Factor (VIF) is calculated before both variables are included into the three-level Over-time Standard APIM simultaneously. The VIF has to be determined in a linear regression model and measures the increase of the variance of a regression coefficient due to multicollinearity of the independent variables (Kutner et al., 2005; Alin, 2010; Backhaus et al., 2016; Salmerón Gómez et al., 2016; Vatcheva et al., 2016). Thereby, multicollinearity is mostly assumed to be given from a value of 10 (Kutner et al., 2005; Alin, 2010; Backhaus et al., 2016; Salmerón Gómez et al., 2016; Vatcheva et al., 2016). However, also a value of 5 is suggested as a cut-off value for multicollinarity (Backhaus et al., 2016; Vatcheva et al., 2016; Hair et al., 2017).

A linear regression for the mental health status is estimated including all independent and all control variables, as a basis for the calculation of the VIF. The results display a mean VIF of 2.21, which is under the critical value of 10 as well as under the alternative critical value of 5 (Kutner et al., 2005; Alin, 2010; Backhaus et al., 2016; Salmerón Gómez et al., 2016; Vatcheva et al., 2016; Hair et al., 2017). Consequently, no multicollinearity is given in the used data and the independent and the control variables can be included into the model simultaneously.[94]

The results of the three-level Full APIM in Table 12, column 2 display that while additionally including the control variables age, education and the occupation dummy variables into the model, the coefficients of the independent variables mainly stay the same. This indicates stable estimation results of the independent variables in the three-level Base APIM.

(a) Spillover Hypotheses

Considering the negative spillover of job insecurity to the mental health status for women (gender = 0) assumed in hypothesis $H1a$, the coefficient of job insecurity is still displayed to be negative (women's actor effect). If women suffer from job insecurity, the mental health status of these women decreases on average by about 1.88 points (about 18.80% of a standard deviation of the mental health status). Hence, women's actor effect is slightly less negative than in the three-level Base APIM by about 0.04 points. Nevertheless, the effect is still significant at the 1%-level of significance. The negative spillover hypothesis for women, $H1a$, is confirmed by the results of the three-level Full APIM controlling for age, education and occupation.

To examine hypothesis $H1b$ and hence the negative spillover of job insecurity to the mental health status for men (gender = 1), the variable measuring job insecurity and the corresponding interaction term with gender (Job Insec.#Gender) has to be considered. The sum of these effects shows that for men who report to experience job insecurity, the mental health status decreases on average by about 2.4 points $(-1.8758 + (-0.4988))$. This corresponds to a decrease of the mental health status by about 24.00% of a standard deviation. Thereby, the actor effect for men in the three-level Full APIM is thus slightly lower than in the three-level Base APIM by about 0.01 points. The joint significance of the variable measuring job insecurity and the corresponding interaction term is tested with an F-Test. The result of this F-Test of joint

[94] A VIF-Test is additionally conducted using the continuous variable, measuring occupation. It results a VIF of 1.21. The results are represented in detail in Table 31 in the Appendix.

significance is displayed in the lower part of Table 12 in column 2 and presents a 1%-level of significance for men's actor effect (F(JI;JI#Gender)). Therefore, hypothesis $H1b$ is confirmed even when the control variables are included into the Over-time Standard APIM.

Regarding hypothesis $H1c$, which assumes the different vulnerability of job insecurity for women and men, a comparison of the effect sizes of women's and men's actor effects have to be conducted. Men's job insecurity is estimated to be stronger related to men's mental health status than women's job insecurity is related to women's mental health status by about 0.50 points. Hypothesis $H1c$ is confirmed by the stronger relationship between job insecurity and the mental health status for men. The three-level Full APIM confirmed both negative spillover hypotheses, while it is controlled for age, education and occupation as well as the different vulnerability of job insecurity across gender to the disadvantage of men.

(b) Crossover Hypotheses

The negative crossover hypothesis for women (gender = 0), $H2a$, is examined under consideration of the estimation result of the variable, which measures partner's job insecurity. It can be seen that the coefficient of this variable, measuring if a women is in a relationship with a man who suffers from job insecurity, is negatively related to women's mental health status (men's partner effect). Thereby, the mental health status of women who are in a relationship with men suffering from job insecurity is on average about 0.64 points lower than for women who are in a relationship with men not suffering from job insecurity. This means a decrease in the mental health status of women on average by about 6.40% of a standard deviation. The difference between men's partner effect in the three-level Full APIM and men's partner effect in the three-level Base APIM solely amounts to 0.01 points. The level of significance does not change as the effect is still significant at the 1%-level of significance in the three-level Full APIM. Hypothesis $H2a$ is still confirmed, even when it is controlled for age, education and occupation.

Regarding the negative crossover hypothesis $H2b$ for men (gender = 1), the variable measuring partner's job insecurity and the corresponding interaction effect with gender (Job Insec. Partner#Gender) has to be taken into account (women's partner effect). The sum of the variables displays that being male and living together with a woman who experiences job insecurity decreases the mental health status on average by about 0.38 points ($-0.6379 + 0.2549$). This corresponds to a decrease of the mental health status by about 3.80% of

a standard deviation. The result is in line with the result of women's partner effect in the three-level Base APIM. However, the effect size of women's partner effect decreases by about 0.02, when the control variables are included into the model. The variable measuring partner's job insecurity and the interaction of this variable with gender is found to be jointly significant at the 1%-level. The joint significance is determined by an F-Test and it's result is displayed in the lower part of Table 12, column 2 (F(PJI;PJI#Gender)). The result confirms hypothesis $H2b$ and hence negative crossover of women's job insecurity to men's mental health status.

The effect sizes of women's and men's partner effects are considered to examine hypothesis $H2c$ and hence, if a woman who is in a relationship with a man who suffers from job insecurity displays a worse mental health status than a man who is in a relationship with a woman who suffers from job insecurity. As already identified in the three-level Base APIM, the decrease of the mental health status is worse for women living with men who suffer from job insecurity, than for men in a relationship with women who experience job insecurity. More detailed, men's partner effect is worse than women's partner effect by about 0.25 points. Therefore, hypothesis $H2c$ is confirmed by the three-Level Full APIM, controlling for age, education and occupation.

(c) Further Results

Gender still displays a significant effect at the 1%-level in the three-level Full APIM. Being male increases the mental health status on average by about 1.82 points (about 18.20% of a standard deviation of the mental health status) which is a slightly lower effect than in the three-level Base APIM. The variable, which captures time trends, becomes significant while including the control variables. The coefficient of the variable measuring age has a positive sign and is highly significant at the 1%-level. An increase in age by one year is on average related to an increase of the mental health status by about 0.08 points (about 0.80% of a standard deviation of the mental health status). If an individual spends one additional year in education, the mental health status of this individual increases on average by about 0.05 points which corresponds to an increase of the mental health status by about 0.50% of a standard deviation of the mental health status. However, the beta coefficient of the variable, which measures the years an individual spends in education, is not significant. Some of the occupation dummy variables again display significant effects. If an individual works as a professional, the mental health status of this individual decreases on average by about 0.62 points (about 6.20% of a standard deviation) in contrast to the case that the individual works in an elementary

occupation. This effect is significant at the 5%-level of significance. Another significant effect, although at the 10%-level of significance, can be found for clerks. Working as a clerk instead of working in an elementary occupation decreases the mental health status on average by about 0.53 points, which means a decrease of about 5.30% of a standard deviation of the mental health status. Working as a legislator, a senior official or a manager as well as working as a technician or an associate professional is also negatively related to the mental health status though not significantly. Working as a service worker, a shop sales worker or a market sales worker as well as working as a skilled agricultural worker, a fishery worker, a craft worker, a trade worker or a plant operator, a machine operator or an assembler is however positively related to the mental health status though also not significantly.

(d) Distribution of Variance and Goodness of Fit

The variance amounts to 56.3997 at level-1, to 14.8617 at level-2 and finally to 25.7156 at level-3. This means that about 58% $((56.3997/(25.7156+14.8617+56.3997))*100)$ of the total variance is due to differences within individuals. Further 15% $((14.8617/(25.7156+14.8617+56.3997))*100)$ of the variance is due to differences within dyads and 27% $((25.7156/(25.7156+14.8617+56.3997))*100)$ of the total variance is due to differences between dyads. The ICC for occasions within individuals and dyads (ICC_{OwIwD}) amounts to 0.42 $(25.7156+14.8617/(25.7156+14.8617+56.3997))$ which equals 42%. The ICC for individuals within dyads (ICC_{IwD}) however amounts to 0.63 $(25.7156/(25.7156+14.8617))$, corresponding to 63%. The ICCs above the critical percent of 10% additionally indicate that it is useful to model occasions at level-1, individuals at level-2, dyads at level-3 and hence, occasions within individuals and individuals within dyads (Lee, 2000; Killip et al., 2004). The relative model fit indices amount to 224,955.3 for the AIC, to 225,122.4 for the BIC and to 224,915.4 for the -2LL value. Therefore, all three relative model fit indices display lower values for the three-level Full APIM compared to those of the three-level Base APIM. This indicates that the three-level Full APIM fits the data better than the three-level Base APIM. The inclusion of the control variables therefore increases the model fit. To determine if the three-level Full APIM is even significantly better than the three-level Base APIM concerning the model fit, a likelihood-ratio test is conducted. The results are represented in Table 14 and display that the null hypothesis H_0 of the likelihood-ratio test, which considers that the three-level Base APIM fits the data significantly better than the three-level Full APIM, can be rejected. Hence, the three-level Full APIM, which includes the control variables age, ed-

ucation and the occupation dummy variables, fits the data even significantly better than the three-level Base APIM without the control variables.[95]

Table 14: Likelihood-Ratio Test – Three-Level Base APIM vs. Three-Level Full APIM

Likelihood-Ratio Test	LR chi2(9) = 98.16
(Assumption: Base APIM nested in Full APIM)	Prob>chi2 = 0.0000

Distinguishability vs. Indistinguishability

Until now, it is assumed that the examined dyads have distinguishable members based on theoretical considerations regarding the Social Role Theory. Following the Social Role Theory, women are assumed to have a stronger identification with the family role than with the work role. Men in contrast are assumed to have a stronger identification with the work role than with the family role (Eagly and Wood, 2011). In summary, this leads to an assumed difference in vulnerability of job insecurity for women and men, which in turn leads the heterosexual members of a dyad being theoretically distinguishable by gender. An empirical examination of the distinguishability of the dyad members is still to be made, but can now be conducted as the three-level Full APIM is developed and estimated.

To determine the assumed distinguishability of the dyad members empirically in a first step, an Over-time Standard APIM has to be estimated, treating the members of a dyad as indistinguishable. In a next step, this model has to be compared to the Over-time Standard APIM, treating them as distinguishable (Kenny et al., 2006). To compare both models, a likelihood-ratio test can be used (Hoffman, 2015). If the Over-time Standard APIM, which treats the dyad members as distinguishable fits the data significantly better, the distinguishability of the members of the observed dyads can not only be theoretically determined, but also be empirically confirmed (Kenny et al., 2006). Therefore, both models are estimated and a likelihood-ratio test with the null hypothesis $H0$, assuming that the Over-time Standard APIM treating the dyad members as indistinguishable fits the data significantly better, is performed. The results of this likelihood-ratio test as well as the values of the relative model fit indices

[95] Additionally, a residual diagnostic of the three-level Full APIM is conducted. The results show, that the residuals at each level have a mean of 0 and are normally distributed. Furthermore, the residuals are determined to be uncorrelated with the independent variables. A test of linearity of the relationship between job insecurity and mental health does not have to be conducted as job insecurity is included as a dummy variable in the three-level Full APIM.

the AIC, the BIC and the -2LL value for each of the models are presented in Table 15. The left column of Table 15 represents the corresponding values for the Over-time Standard APIM, treating the dyad members as distinguishable. The right column however represents the corresponding values for the Over-time Standard APIM, treating the dyad members as indistinguishable. The result of this likelihood-ratio test displays that the null hypothesis $H0$ can be rejected. Hence, the model treating the dyad members as distinguishable, fits the data significantly better than the one treating them as indistinguishable. This result is additionally supported by comparing the AIC, the BIC and the -2LL value, because the values for the Over-time Standard APIM, which treats the dyad members as distinguishable, display lower values than those for the Over-time Standard APIM, treating them as indistinguishable.

Table 15: Distinguishability vs. Indistinguishability

	Three-Level Over-time Standard APIM	
	(1)	(2)
	Distinguishable Members	Indistinguishable Members
AIC	224955.3	225110.2
BIC	225122.4	225252.2
-2 Log likelihood	224915.4	225076.2
Likelihood-Ratio Test	LR chi2(3) = 160.85	
(Assumption: Indis.nested in Dis.)	Prob>chi2 = 0.0000	

Number of Obs.: 31,316, Number of Individuals: 12,826, Number of Dyads: 6,376. Dependent variable: MCS. Estimation procedure: ML. All control variables are included.

7.2.1.3 Robustness Checks

After the presentation of the estimation results of the Base and the Full APIM for job insecurity and the mental health status, some robustness checks are conducted in the following to approach a causal interpretation between job insecurity, partner's job insecurity and the mental health status. Previous research identifies four necessary conditions, which have to be fulfilled for a causal interpretation between two variables (Kube, 1991; Hildebrandt et al., 1992; Haenecke, 2002; Herrmann et al., 2008; Trommsdorff and Teichert, 2011; Döring and Bortz, 2016).[96] The first condition demands that the hypothesis

[96] Further references are Simon (1954), Zimmermann (1972), Hunt (1976), Hildebrandt (1983b) and Hildebrandt (1983a).

of the relationship between both variables has to be derived theoretically. Additionally, an empirical correlation between the hypothesized variables has to be present. The third condition requires that a temporal asymmetry between both variables exists and the fourth condition finally requires that effects due to additional variables have to be excluded (Kube, 1991; Hildebrandt et al., 1992; Haenecke, 2002; Herrmann et al., 2008; Trommsdorff and Teichert, 2011; Döring and Bortz, 2016). Up to this point, it is already shown, that job insecurity and partner's job insecurity theoretically affect the mental health status of an individual by presenting the Spillover-Crossover Model (see Chapter 2). Additionally, an empirical correlation between job insecurity, partner's job insecurity and the mental health status is demonstrated (see Chapter 7.2.1.2). Hence, to approach a causal interpretation between job insecurity, partner's job insecurity and the mental health status, the existence of a temporal asymmetry between the variables and the exclusion of effects due to additional variables is still pending. Therefore, some robustness checks regarding temporal asymmetry, unobserved heterogeneity and omitted variable bias will be conducted.

Three-Level Lag Model

First, to examine if a temporal asymmetry between job insecurity, partner's job insecurity and the mental health status exists, the three-level Over-time Standard APIM will be estimated including $t-1$ lag variables of the independent variables job insecurity and partner's job insecurity. Hereinafter, this model will be referred to as three-level Lag Model. Because the mental health status is measured in the years 2002, 2004, 2006, 2008, 2010 and 2012, job insecurity and partner's job insecurity of the years 2001, 2003, 2005, 2007, 2009 and 2011 are used as $t-1$ lag variable for each of the years the mental health status is measured. Due to the fact that not all individuals are observed in each year, some observations are lost due to missing information about job insecurity and partner's job insecurity in $t-1$. The number of observations in the three-level Lag Model accounts to 25,118. Hence, 6,198 observations which amounts to about 20% of all observations are lost, because of missing information. Nevertheless, still 5,147 dyads and 10,294 individuals are included into the analysis. The results of the three-level Lag Model of job insecurity and partner's job insecurity are represented in Table 16. Thereby, with exception of the $t-1$ lag variables, the model corresponds to the three-level Full APIM, presented in Table 12 and hence the three-level Lag Model also includes the control variables age, education and occupation.

Table 16: Three-Level Lag Model

	Three-Level $t-1$ Lag Model
Constant	49.9426***
	(0.3427)
Gender	1.8425***
	(0.2068)
Job Insecurity in t-1	-1.0613***
	(0.1783)
Partner Job Insecurity in t-1	-0.3608**
	(0.1807)
Job Insec. t-1#Gender	-0.6817***
	(0.2557)
Job Insec. t-1 Partner#Gender	0.2695
	(0.2555)
Time	-0.0738**
	(0.0376)
Age	0.0825***
	(0.0103)
Yrs in Education	0.0659*
	(0.0389)
Legislators/Senior Officials/Managers	0.1447
	(0.3801)
Professionals	-0.4154
	(0.3551)
Techn./Assoc. Profess.	-0.0646
	(0.3097)
Clerks	-0.3221
	(0.3352)
Service/Sales Workers	0.4160
	(0.3406)
Agric./Fishery/Craft/Trade Workers	0.0019
	(0.3302)
Plant/Machine Operators/Assemblers	0.5437
	(0.3747)

Table 16 (continued): Three-Level Lag Model

Level 3 Variance	27.2299***
	(0.5494)
Level 2 Variance	15.3994***
	(0.4992)
Level 1 Variance	55.5274***
	(0.4153)
F(JI_{t-1};JI_{t-1}#Gender)	128.38***
F(PJI_{t-1};PJI_{t-1}#Gender)	4.27
AIC	180488.7
BIC	180651.3
-2 Log likelihood	180448.8
Number of Observations	25,118
Number of Individuals	10,294
Number of Dyads	5,147

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Dependent variable: MCS in t. Estimation procedure: ML. Base category for Gender: Men. Base category for occupation dummy variables: Elementary occupations.

(a) Spillover Hypotheses

Regarding hypothesis $H1a$, which assumes the spillover of job insecurity to the mental health status for women (gender = 0), it can be seen that the negative relationship between job insecurity and the mental health status even remains, when the experience of job insecurity is made in $t-1$. If women suffer from job insecurity in $t-1$, their mental health status in t is on average about 1.06 points lower, which corresponds to a decrease of about 10.60% of a standard deviation of the mental health status (women's actor effect). The coefficient of the variable measuring job insecurity in $t-1$ is significant at the 1%-level of significance and therefore confirms the negative spillover hypothesis $H1a$.

To examine the negative actor effect from job insecurity to the mental health status for men (gender = 1) within hypothesis $H1b$, the sum of the coefficients of the variable, measuring job insecurity in $t-1$ and the associated interaction term with gender (Job Insec. in t-1#Gender) have to be considered. For men, the mental health status decreases on average by about 1.74 points $(-1.0613 + (-0.6817))$, which corresponds to a decrease of about 17.40% of a standard deviation of the mental health status (men's actor effect). The joint significance of the variable, measuring job insecurity in $t-1$ and the interaction between this variable and gender (Job Insec. in t-1#Gender) is found to be

significant at the 1%-level of significance. The significance of the interaction is tested using an F-Test of joint significance displayed in the lower part of Table 16 (F(JI_{t-1};JI_{t-1}#Gender)). Hypothesis $H1b$ and hence the negative spillover of job insecurity to the mental health status for men is confirmed.

Considering hypothesis $H1c$ and hence the assumption that the mental health status of a man who suffers from job insecurity is worse than the mental health status of a woman who suffers from job insecurity, the effects sizes of women's and men's actor effects have to be taken into consideration. The comparison of both effect sizes displays that the actor effect of men is more negative than the actor effect of women by about 0.68 points. This leads to the confirmation of hypothesis $H1c$ for job insecurity experienced in $t-1$.

(b) Crossover Hypotheses

Hypothesis $H2a$ deals with the negative crossover of men's job insecurity in $t-1$ to women's mental health status in t (men's partner effect) and is therefore examined for women (gender=0) under the consideration of the variable, measuring partner's job insecurity in $t-1$. The result of this variable in Table 16 displays that the partner effect from men's job insecurity in $t-1$ to women's mental health status in t is related to a decreased mental health status of women in t by on average about 0.36 points, which equals to a decrease by about 3.60% of a standard deviation of the mental health status. Men's partner effect is still significant at the 5%-level and hypothesis $H2a$ is in line with the estimation results of the three-level Lag Model.

Regarding hypothesis $H2b$ and hence the negative crossover of women's job insecurity in $t-1$ to men's mental health status in t (women's partner effect), the variable measuring partner's job insecurity in $t-1$ and the corresponding interaction of this variable with gender (Job Insec. Partner#Gender) have to be considered. It appears, that women's partner effect decreases the mental health status of men in t on average by about 0.09 points ($-0.3608+0.2695$), which corresponds to a decrease of the mental health status of men in t by about 0.90% of a standard deviation. The partner effect from women to men still displays a negative coefficient sign, but the effect is no longer significant in the three-level Lag Model. The insignificance is represented by an F-Test of joint significance of the variable measuring partner's job insecurity and the corresponding interaction term with gender (Job Insec. Partner#Gender), displayed in the lower part of Table 16 (F(PJI_{t-1};PJI_{t-1}#Gender)). Therefore, hypothesis $H2b$ can not be confirmed in the three-level Lag Model. The assumption that if a man is in a relationship with a woman who suffers from job

insecurity in $t-1$, the mental health status of this man in t is worse than the mental health status of a man in a relationship with a woman who does not suffer from job insecurity in $t-1$, is not supported by the estimation results.

With respect to the assumed gender differences of the partner effects in hypothesis $H2c$, the results display that men's job insecurity in t is more negatively related to women's mental health in $t-1$ than women's job insecurity in t to men's mental health in $t-1$ by about 0.30 points. However, as determined, the relation between women's job insecurity in $t-1$ and men's mental health status in t is not significant. Summarized, hypothesis $H2c$ considering the different vulnerability regarding crossover of job insecurity to the mental health status across gender is in line with the results of the three-level Lag Model. The partner effect from men to women is displayed to be significant and more harmful than the partner effect from women to men.

(c) Further Results

The variable, controlling for gender is still significant at the 1%-level of significance in the three-level Lag Model. The effect size however deviates from the effect size estimated in the three-level Full APIM by about 0.02 points. The larger estimation can be found in the three-level Lag Model. The significance level of the variable capturing time trends is still significant like in the three-level Full APIM. Regarding the control variables, age is still identified to be significantly positive related to the mental health status in the three-level Lag Model. An additional year in age increases the mental health status of an individual on average by about 0.08 points (about 0.80% of a standard deviation of the mental health status). However, the deviation from the estimation result in the three-level Full APIM is minor, because it is just visible at the third decimal place. The variable measuring the years an individual spends in education displays a significant positive effect in the three-level Lag Model. In the Full APIM, the variable is also positive but not significant. In the three-level Lag Model however, the years an individual spends in education are significantly related to the mental health status at a 10%-level of significance. The deviation in the effect sizes amounts to 0.02 points with a higher effect size in the three-level Lag Model. The occupation dummy variables measuring if an individual works as a professional as well as the dummy variable measuring if an individual works as a clerk are no longer significant in the three-level Lag Model compared to the Full APIM. Thereby, the coefficient signs remain negative and the effect sizes deviate by 0.20 respectively 0.21. For both occupation dummy variables, the effect sizes estimated in the three-level Full APIM are larger than those estimated in the three-level Lag

Model. The dummy variable, measuring if an individual works in the occupation group of service workers, shop sales workers and market sales workers, is still positively related to the mental health status. The same is true for the dummy variable measuring if an individual works in the occupation group of skilled agricultural workers, fishery workers, craft workers and trade workers as well as in the occupation group of plant operators, machine operators and assemblers. However, the effects of these occupation dummy variables are still insignificant. The occupation dummy variable, measuring if an individual is working in the occupation group of legislators, senior officials and managers is no longer negatively related to the mental health status as the estimation result of the three-level Lag Model represents a positive coefficient sign. However, the insignificance of this occupation dummy variable already identified in the three-level Full APIM remains. The effect sizes of the variables measuring if individuals are working as legislators, senior officials, managers, service workers, shop sales workers, market sales workers, plant operators, machine operators and assemblers are higher in the three-level Lag Model than in the three-level Full APIM. For the four remaining occupation dummy variables, the estimation of the effect sizes is higher in three-level Full APIM than in the three-level Lag Model.

(d) Goodness of Fit and Closing Summary

Considering the relative model fit indices, the AIC displays a value of 180,488.7, the BIC a value of 180,651.3 and the -2LL a value of 180,448.8. In comparison to the model fit indices of the three-level Full APIM, the indices of the three-level Lag Model show lower values, indicating a better model fit for the three-level Lag Model. A significant better model fit can not be determined conducting a likelihood-ratio test, because the assumption of the test is not fulfilled. The assumption that one of the models has to be an extension of the other model is not given considering the three-level Full APIM and the three-level Lag Model.[97] Comprehensively, the results of the three-level Lag Model display that previous job insecurity of women as well as previous job insecurity of men are significantly related to the current mental health status of women and men. This finding contributes to detect temporal asymmetry between job insecurity and the mental health status. However, temporal asymmetry between partner's job insecurity and the mental health status is only identified if men are suffering from job insecurity in $t-1$.

[97] For more information see Snijders and Bosker (2012).

Three-Level Hybrid Model

To approach condition four for a causal interpretation and hence the exclusion of effects due to additional variables, it is necessary to control for variables that can have a potential influence on the relationship between job insecurity and the mental health status. Three additional variables, which are assumed to have influence on the relationship, are already controlled for in the Full APIM, since the control variables age, education and occupation are included. Nevertheless, it is possible that the relationship is influenced by additional variables that are observable but not yet included, called omitted variables. Furthermore, unobservable characteristics may influence the estimated relationship between job insecurity and the mental health status, known as unobserved heterogeneity. To approach these variables, it is possible to conduct a robustness check regarding omitted variable bias and unobserved heterogeneity as the used data is longitudinal. Generally, using longitudinal data Random-Effects and Fixed-Effects Models could be estimated to do so. Random-Effects and Fixed-Effects Models control for unobserved heterogeneity and solve the problem of omitted variable bias, no matter if observed or unobserved (Wooldridge, 2010; Morgan, 2013). Thereby, Random-Effects Models capture the unobserved heterogeneity which is random across individuals. Fixed-Effects Models however capture the unobserved heterogeneity across individuals which is fixed over time. The main disadvantage of Fixed-Effects Models is the limitation that only time varying variables can be included into a Fixed-Effects Model (Wooldridge, 2010; Morgan, 2013). In a Random-Effects Model, effects of time-varying and time constant variables can indeed be estimated, but it is not possible to control for fixed unobserved heterogeneity (Wooldridge, 2010; Morgan, 2013).

While using a Fixed-Effect Model in the present analysis to capture unobserved heterogeneity, it is not possible to estimate one of the variables of main interest, the time-invariant variable of gender. Therefore, it is not useful to estimate such a Fixed-Effects Model. Due to the fact that it is furthermore not known if unobserved heterogeneity, when present in the data, is due to random or fixed effects, a Random-Effects Model should also not be estimated exclusively. In multilevel models with independent and control variables that are either time-varying or constant over time, like in the three-level Full APIM above, a three-level Hybrid Model can be estimated, which combines the advantages of Random-Effects Models and Fixed-Effects Models (Krause and Urban, 2013). To estimate a three-level Hybrid Model, the time-varying variables have to be differentiated into a within-individual part and a between-individual

part. The within-individual part of a variable represents the change of the variable value within each individual. The between-individual part however displays the average value of the variable of each individual and the variation of this average value between the individuals (Krause and Urban, 2013). Due to this separation, the effect of the within-individual part and the effect of the between-individual part of a variable are no longer related to a constant time indicator and hence are no longer related to other independent variables, which could not be included into the model (omitted variables). Therefore, the coefficients are no longer biased due to omitted variables or unobserved heterogeneity (Krause and Urban, 2013). Hence, it is controlled for effects due to additional variables required by Kube (1991), Hildebrandt et al. (1992), Haenecke (2002), Herrmann et al. (2008), Trommsdorff and Teichert (2011), Döring and Bortz (2016).

Nevertheless, there is also a disadvantage of the three-level Hybrid Model as the estimation of such a model is associated with a loss of estimation power. Individuals with no change in the time-varying variables do not contribute to the estimation of the within-individual part of this variable (Krause and Urban, 2013). Regarding the following analysis, this means that individuals who do not change between the status of *job insecurity* and the status of *no job insecurity* could not be used to estimate the effect of the within-individual part of the variable job insecurity. Of the 31,316 individual-year observations, 11,769 observations can be traced back to individuals who change between the status of experiencing job insecurity and the status of not experiencing job insecurity. Hence, the within-individual effect of job insecurity is estimated with 11,769 observations, which corresponds to about 38% of the used individual-year observations above, comprising 2,295 dyads.

The results of a three-level Hybrid Model are represented in Table 17. All control variables of the three-level Full APIM are also included into the three-level Hybrid Model. The variable *Job Insecurity_Mean* displays the between-individual part of the variable measuring job insecurity. The variable *Job Insecurity Partner_Mean* represents the between-individual part of the variable measuring partner's job insecurity. The between-individual parts of the variables are not of interest for content-related interpretation, but the estimations of these variables can be used as reference for the within-individual parts of the regarding variables. If a significant difference between the estimations of the within-individual part and of the between-individual part of a variable exists, it can be assumed that unobserved heterogeneity is present in the used data (Krause and Urban, 2013).

Table 17: Three-Level Hybrid Model

	Three-Level Hybrid Model
Constant	52.0108***
	(0.3132)
Gender	1.7307***
	(0.1353)
Job Insecurity_Mean	-3.9570***
	(0.2311)
Job Insecurity Partner_Mean	-0.6790***
	(0.2295)
Δ Job Insecurity	-0.9737***
	(0.2040)
Δ Job Insecurity Partner	-0.4956***
	(0.1895)
Δ Job Insec.#Gender	-0.3334
	(0.2943)
Δ Job Insec. Partner#Gender	0.3219
	(0.2268)
Time	-0.0816**
	(0.0325)
Age	0.0725***
	(0.0087)
Yrs in Education	0.0181
	(0.0343)
Legislators/Senior Officials/Managers	-0.1667
	(0.3334)
Professionals	-0.7839**
	(0.3112)
Techn./Assoc. Profess.	-0.3278
	(0.2716)
Clerks	-0.5814**
	(0.2939)
Service/Sales Workers	0.2527
	(0.2992)
Agric./Fishery/Craft/Trade Workers	0.0901
	(0.2893)
Plant/Machine Operators/Assemblers	0.4702
	(0.3308)

Table 17 (continued): Three-Level Hybrid Model

Level 3 Variance	25.1730***
	(0.4730)
Level 2 Variance	14.7635***
	(0.4422)
Level 1 Variance	56.3264***
	(0.3725)
F(ΔJI;ΔJI#Gender)	59.92***
F(ΔPJI;ΔPJI#Gender)	6.92**
AIC	224832.3
BIC	225016.0
-2 Log likelihood	224788.2
Number of Observations	31,316
Number of Individuals	12,826
Number of Dyads	6,376

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Dependent variable: MCS. Estimation procedure: ML. Base category for Gender: Men. Base category for occupation dummy variables: Elementary occupations.

The variable Δ *Job Insecurity* and the variable Δ *Job Insecurity Partner* represent the within-individual parts of the variable, measuring job insecurity respectively partner's job insecurity. They can be interpreted as the change of an individual from *no job insecurity* to *job insecurity*. While comparing the actor and partner effects of women and men from the three-level Hybrid Model with those of the three-level Full APIM in the following, it has to be taken into consideration, that the Hybrid Model does not estimate the general effect of job insecurity like it is done in the three-level Full APIM, but the within-individual part of job insecurity. Nevertheless, a comparison should be conducted, to enable an understanding of the differences.

(a) Spillover Hypotheses

Regarding negative spillover of job insecurity to the mental health status for women (gender = 0) and hence hypothesis $H1a$, the estimation results in Table 17 show that the within-individual part of the variable job insecurity (Δ *Job Insecurity*) is negatively related to the mental health status (women's actor effect). This displays that if a woman changes from a situation of *no job insecurity* to a situation of *job insecurity*, the mental health status of this woman decreases on average by about 0.97 points. This effect size corresponds to about 9.70% of a standard deviation of the mental health status. Due to the significance of this effect at the 1%-level of significance, hypothesis $H1a$ and

hence, a worse mental health status for women who suffer from job insecurity compared to women who do not suffer from job insecurity, can be confirmed by the three-level Hybrid Model.

To examine the negative spillover of job insecurity for men (gender = 1) assumed by hypothesis $H1b$, the sum of the within-individual part of the variable job insecurity (Δ *Job Insecurity*) and the interaction effect of this variable with gender (Δ *Job Insec.#Gender*) has to be considered (men's actor effect). It can be seen that, if a man changes from a situation of *no job insecurity* to a situation of *job insecurity*, the mental health status of this man decreases on average by about 1.31 points ($-0.9737 + (-0.3334)$). This equals to a decrease by about 13.10% of a standard deviation of men's mental health status. The joint significance of the within-individual part of the variable job insecurity and the corresponding interaction term with gender (Δ Job Insec.#Gender) displays a significance at the 1%-level. Again, the significance of the interaction is tested using an F-Test. The result of this F-Test is displayed in the lower part of Table 17 (F(ΔJI;ΔJI#Gender)). A significant negative relationship between job insecurity and the mental health status for men can still be identified in the three-level Hybrid Model. More precisely, a change in the variable measuring job insecurity from „0“ (*no job insecurity*) to „1“ (*job insecurity*) is negatively related to the mental health status of men. Hypothesis $H1b$ can still be confirmed, when it is controlled for unobserved heterogeneity and omitted variable bias.

Comparing the effect sizes of women's and men's actor effects to examine the assumed different vulnerability of job insecurity across gender considered by hypothesis $H1c$, the results display that the relationship between job insecurity and the mental health status is stronger for male individuals than for female individuals. Men's job insecurity is more negatively related to the mental health status of men by about 0.33 points than women's job insecurity to women's mental health status. The results of the three-level Hybrid Model confirm Hypothesis $H1c$ and hence the different vulnerability of job insecurity for women and men to the disadvantage of men.

(b) Crossover Hypotheses

Examining the negative crossover of men's job insecurity on women's mental health status within hypothesis $H2a$, the coefficient of the variable, measuring a change from a relationship with a partner who does not suffer from job insecurity to a relationship with a partner who suffers from job insecurity[98] (Δ

[98] Here, not necessarily the partner has to be changed, but the experiences of job insecurity of the partner. Both opportunities are possible.

Job Insec. Partner), has to be taken into consideration (men's partner effect). The coefficient of this variable displays that a change from a relationship with a man who does not suffer from job insecurity to a relationship with a man who suffers from job insecurity decreases the mental health status of women on average by about 0.50 points (about 5.00% of a standard deviation of the mental health status). This effect is found to be significant at the 1%-level of significance. This means, a significant negative relationship between men's job insecurity and women's mental health status still exists, when it is controlled for unobserved heterogeneity and omitted variable bias. Hypothesis $H2a$ can be confirmed.

The sum of the coefficients of the variable, measuring a change from a relationship with a partner who does not suffer from job insecurity to a relationship with a partner who suffers from job insecurity, and the associated interaction term of this variable with gender (Δ Job Insecurity Partner#Gender) has to be regarded in terms of hypothesis $H2b$ (women's partner effect). A change from a relationship with a woman who does not suffer from job insecurity to a relationship with a woman who suffers from job insecurity decreases the mental health status of men on average by about 0.17 points ($-0.4956 + 0.3219$) and hence about 1.70% of a standard deviation. This effect is found to be significant at the 5%-level of significance, represented by the result of an F-Test of joint significance for partner's job insecurity and the corresponding interaction term (F(ΔPJI;ΔPJI#Gender)). Hence, hypothesis $H2b$ can be confirmed. A negative crossover of womens's job insecurity on men's mental health status is verified by the estimation results of the three-level Hybrid Model.

Hypothesis $H2c$ considers the worse mental health status of a woman in a relationship with a man who suffers from job insecurity compared to the mental health status of a man who is in a relationship with a woman who suffers from job insecurity. To examine hypothesis $H2c$, a comparison of the effect sizes of women's and men's partner effects is conducted. A stronger relation between men's job insecurity and women's mental health status than between women's job insecurity and men's mental health status by about 0.32 points can be detected. Both effects are still significant, when controlling for unobserved heterogeneity and omitted variable bias, though the effect for men is now significant at the 5%-level. Nevertheless, hypothesis $H2c$ and hence the different vulnerability of job insecurity for women and men is confirmed by the three-level Hybrid Model, controlling for unobserved heterogeneity and omitted variable bias.

(c) Further Results

The estimated effect size of the variable measuring gender is found to be smaller in the three-level Hybrid Model than in the three-level Full APIM. The deviation amounts to about 0.09 points. However, the significance of the effect still remains at the 1%-level of significance. Also the level of significance of the variable controlling for time trends remains at the 5%-level of significance. The control variable measuring an individuals' age still displays a significant positive relation to the mental health status. The deviation from the estimation of the three-level Full APIM only appears in the third decimal place of the effect size. The effect size of the variable measuring the years an individual spends in education decreases by about 0.03 points, once it is controlled for unobserved heterogeneity and omitted variable bias in the three-level Hybrid Model. However, the relationship is still insignificant like in the three-level Full APIM. Regarding the occupation dummy variables, the coefficient signs do not change when it is controlled for unobserved heterogeneity and omitted variable bias. Additionally, the dummy variables, which measure if an individual works in the occupation group of professionals and the one which measures if an individual works as a clerk, still display significant effects in the three-level Hybrid Model. The other occupation dummy variables remain insignificant. The effect sizes of all occupation dummy variables deviate from the estimation results of the Full APIM. The effect sizes of the variable, controlling for the occupation group of service workers, shop sales workers and market sales workers decrease. The same is true for the dummy variable measuring if an individual works in the occupation group of skilled agricultural workers, fishery workers, craft workers and trade workers. For all other occupation dummy variables the three-level Hybrid Model displays higher effect sizes compared to the three-level Full APIM.

(d) Goodness of Fit and Closing Summary

Regarding the relative model fit indices which are displayed in the lower part of Table 17, the AIC value of the three-level Hybrid Model amounts to 224,832.3. The BIC value and the -2LL value amount to 225,016.0, respectively 224,788.2. Comparing the relative model fit indices of the three-level Hybrid Model with those of the three-level Full APIM above, it can be seen that the AIC and the BIC values as well as the -2LL value are slightly lower in the three-level Hybrid Model than in the three-level Full APIM. This indicates a better model fit of the three-level Hybrid Model. The significant difference between the within-individual part of the variable measuring job insecurity and the between-individual part of this variable additionally indicates that unobserved

heterogeneity in the data exists and needs to be controlled for. A likelihood-ratio test to investigate whether the differences between both model fits are even significant can not be conducted. The condition that one of the models has to be an extension of the other model is not met here.[99] Comprehensively, even if the effect sizes of the changes in job insecurity and partner's job insecurity are below those of the general effect of job insecurity and partner's job insecurity in the three-level Full APIM, the results of the three-level Hybrid Model are in line with all six assumed hypotheses. Significant relationships between the change in job insecurity respectively partner's job insecurity and the mental health status can be found for women and for men, while it is controlled for unobserved heterogeneity and omitted variable bias.

7.2.2 Two-Level Modeling

7.2.2.1 Empirical Results

Table 18 represents the results of a two-level Over-time Standard APIM with individuals at level-1 and dyads at level-2, whereas it is assumed that occasions are fully crossed within individuals and individuals in turn are nested within dyads. Column 1 of Table 18 displays the results of the two-level Over-time Standard APIM, if only the independent variables are included into the model as well as the variable measuring time. In the following, this model will be referred to as two-level Base APIM. Column 2 however demonstrates the results, if the control variables measuring age, education and occupation based on the ISCO are additionally considered. Hereinafter, this model will be referred to as two-level Full APIM.

Two-Level Base APIM

(a) Spillover Hypotheses

Regarding hypothesis $H1a$ and hence the negative spillover of job insecurity to the mental health status for women (gender = 0), the results in column 1 show that job insecurity is significantly related to the mental health status (women's actor effect). Job insecurity experienced by women decreases their mental health status on average by about 1.93 points, which corresponds to a decrease in the mental health status by about 19.30% of a standard deviation of the mental health status. The effect is significant at the 1%-level of significance. Hence, hypothesis $H1a$ can be confirmed in the two-level Base APIM.

[99] For more information see Snijders and Bosker (2012).

Table 18: Two-Level Over-time Standard APIM

	Two-Level	
	(1)	(2)
	Base APIM	Full APIM
Constant	50.2858***	50.9825***
	(0.1860)	(0.3039)
Gender	2.1547***	1.8993***
	(0.1766)	(0.1846)
Job Insecurity	-1.9303***	-1.8806***
	(0.1646)	(0.1648)
Job Insecurity Partner	-0.6905***	-0.6741***
	(0.1674)	(0.1675)
Job Insec.#Gender	-0.6117***	-0.6543***
	(0.2282)	(0.2288)
Job Insec. Partner#Gender	0.2431	0.2477
	(0.2276)	(0.2276)
Time	0.0024	-0.0991***
	(0.0306)	(0.0324)
Age		0.0790***
		(0.0086)
Yrs in Education		0.0476
		(0.0339)
Legislators/Senior Officials/Managers		-0.0917
		(0.3321)
Professionals		-0.6631**
		(0.3105)
Techn./Assoc. Profess.		-0.2605
		(0.2725)
Clerks		-0.5549*
		(0.2957)
Service/Sales Workers		0.2767
		(0.3018)
Agric./Fishery/Craft/Trade Workers		0.0643
		(0.2883)
Plant/Machine Operators/Assemblers		0.4081
		(0.3294)

Table 18 (continued): Two-Level Over-time Standard APIM

Level 2 Variance - Women	43.1542***	42.3688***
	(0.8161)	(0.8112)
Level 2 Variance - Men	31.9710***	30.8520***
	(0.7507)	(0.7442)
Level 1 Variance	55.3193***	55.3523***
	(0.3802)	(0.3810)
F(JI;JI#Gender)	361.27***	346.67***
F(PJI;PJI#Gender)	24.63***	22.98***
AIC	224964.3	224880.2
BIC	225114.6	225105.7
-2 Log likelihood	224928.4	224826.2
Number of Observations	31,316	31,316
Number of Individuals	12,826	12,826
Number of Dyads	6,376	6,376

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Dependent variable: MCS. Estimation procedure: ML. Base category for Gender: Men. Base category for occupation dummy variables: Elementary occupations.

To examine hypothesis $H1b$ and hence the negative spillover of job insecurity to the mental health status for men (gender = 1), the variable measuring job insecurity and the corresponding interaction term with gender (Job Insec.#Gender) have to be considered (men's actor effect). The actor effect of men is determined by the sum of the coefficient of the variable, measuring job insecurity and the corresponding interaction effect with gender $(-1.9303 + (-0.6117))$. Men who suffer from job insecurity have on average a lower mental health status of about 2.54 points, than men who do not suffer from job insecurity. The effect displays a decrease in the mental health status by about 25.40% of a standard deviation. As already used in the three-level Over-time Standard APIMs, the significance of the interaction is determined using an F-Test of joint significance of job insecurity and the corresponding interaction term with gender. The result of the F-Test is represented in the lower part of Table 18 and displays a significance at the 1%-level of significance ($F(JI; JI\#Gender)$). Hence, hypothesis $H1b$ considering negative spillover of job insecurity to the mental health status for men can additionally be confirmed.

To examine the different vulnerability of job insecurity for women and men and hence hypothesis $H1c$, the effect sizes of women's and men's actor effects are considered. The results display that hypothesis $H1c$ can be confirmed, because

men's job insecurity is stronger related to men's mental health status than women's job insecurity to women's mental health status by about 0.61 points. Therefore, the two-level Base APIM confirms the negative spillover hypotheses of job insecurity as well as the different vulnerability of job insecurity across gender to the disadvantage of men.

(b) Crossover Hypotheses

Regarding hypothesis $H2a$, and hence the crossover of job insecurity to the mental health status for women (gender = 0), the results display that the coefficient of the variable measuring partner's job insecurity is negatively related to the mental health status (men's partner effect). Job insecurity of men decreases the mental health status of women on average by about 0.69 points and hence by about 6.90% of a standard deviation of women's mental health status. This effect is displayed to be significant at the 1%-level of significance. Hypothesis $H2a$ and therefore the crossover of job insecurity to the mental health status for women is confirmed by the two-level Base APIM.

Considering the crossover of job insecurity to the mental health status for men (gender = 1) assumed in hypothesis $H2b$, the interaction of the variable measuring partner's job insecurity with gender (Job Insec. Partner#Gender) has to be additionally considered (women's partner effect). The sum of the coefficients displays that the partner effect from women's job insecurity to men's mental health status decreases the mental health status of men on average by about 0.45 points $(-0.6905 + 0.2431)$. This corresponds to a decrease of the mental health status by about 4.50% of a standard deviation. Women's partner effect is also found to be significant at the 1%-level. The significance of the interaction between partner's job insecurity and gender is thereby again tested using an F-Test of joint significance of the variable measuring partner's job insecurity and the associated interaction term with gender (Job Insec. Partner#Gender). The result of this F-Test is displayed in the lower part of Table 18 by F(PJI;PJI#Gender). Summarized, hypothesis $H2b$ is confirmed by the two-level Base APIM.

The effect sizes of women's and men's partner effects are considered in the following to examine hypothesis $H2c$ and hence the different vulnerability regarding the crossover of job insecurity for women and men. The relationship between men's job insecurity and women's mental health status is stronger than the relationship between women's job insecurity and men's mental health status by about 0.24 points. Hypothesis $H2c$ can be confirmed by the results of the two-level Base APIM. Summarized, the two-level Base APIM therefore

supports the negative crossover hypotheses as well as the different vulnerability of job insecurity across gender to the disadvantage of men.

(c) Further Results

Another significant effect displayed in Table 18 can be found for the variable measuring gender. The results display that being male (gender = 1) increases the mental health status on average by about 2.15 points and hence by about 21.50% of a standard deviation of the mental health status. This relationship is significant at the 1%-level of significance. The variable included to capture time trends is however not significant.

(d) Distribution of Variance and Goodness of Fit

The proportion of variance at the different levels of the model are represented in the lower part of Table 18. In the two-level Base APIM, the level-2 variance is differentiated between women and men, because the variance in the dependent variable may differ across the distinguishing variable gender (see Chapter 8, Kenny and Kashy (2011)). Considering women, 56% $((55.3193/(55.3193+43.1542))*100)$ of the total variance is due to differences between individuals and 44% $((43.1542/(55.3193+43.1542))*100)$ is due to differences between dyads. Considering men, 63% $((55.3193/(55.3193+31.9710))*100)$ of the total variance goes back to differences between individuals and 37% $((31.9710/(55.3193+31.9710))*100)$ to differences between dyads. The relative model fit indices, also displayed in the lower part of Table 18, become relevant when comparing the two-level Base APIM and the two-level Full APIM. The AIC amounts to 224,964.3, the BIC to 225,114.6 and the -2LL value amounts to 224,928.4.

Two-Level Full APIM

Moving from the Base APIM to the Full APIM, it is not necessary to control for multicollinearity again, as the VIF was already conducted in Chapter 7.2.1.2. The results of the VIF are independent of the number of levels which are introduced, because the VIF is determined in a linear regression model.[100] The estimation results of the two-level Full APIM represented in column 2 display that the coefficients of the independent variables are close to the one in column 1. Hence, the results of the independent variables are relatively stable even when including the control variables age, education and the occupation

[100] The results are represented in Table 31 in the Appendix.

dummy variables based on the ISCO.[101]

(a) Spillover Hypotheses

Considering the negative spillover of job insecurity to the mental health status for women (gender = 0) assumed in hypothesis $H1a$, the coefficient of job insecurity is displayed to be negative (women's actor effect). If a woman suffers from job insecurity, the mental health status of this woman is on average by about 1.88 points lower than the mental health status of a woman who does not suffer from job insecurity. This corresponds to a decrease of the mental health status of women on average by about 18.80% of a standard deviation. When it is controlled for age, education and occupation, the effect is slightly lower by about 0.05 points than in the two-level Base APIM, but still significant at the 1%-level of significance. Hypothesis $H1a$ is confirmed, as the results display a significant negative actor effect of women.

Hypothesis $H1b$ assumes a worse mental health status for men who suffer from job insecurity than for men who do not suffer from job insecurity. To examine this hypothesis, two coefficients are of interest. The coefficients of the variable measuring job insecurity and the interaction term of job insecurity and gender (Job Insec.#Gender). The sum of the coefficients displays that job insecurity of men is on average related to a decreased mental health status of men by about 2.53 points $(-1.8806 + (-0.6543))$. This corresponds to a decrease by about 25.30% of a standard deviation (men's actor effect). In the two-level Full APIM, the actor effect of men is about 0.04 points higher than in the two-level Base APIM. The significance of the interaction is again tested using an F-Test of joint significance for job insecurity and the corresponding interaction term (Job Insec.#Gender). The result is represented in the lower part of Table 18 by F(JI;JI#Gender) and displays a significance for men's actor effect at the 1%-level of significance. This leads to a confirmation of the negative spillover hypothesis $H1b$ of job insecurity to the mental health status for men, even when it is controlled for age, education and occupation in the two-level Full APIM.

Regarding hypothesis $H1c$ and hence the different vulnerability of job insecurity for women and men, the comparison of the effect sizes of women's and men's actor effects are of particular interest. The results display, that the difference between women's actor effect and men's actor effect in favor to women

[101] It is not necessary to empirically determine the distinguishability of the dyad members again while using a two-level Over-time Standard APIM. The distinguishability is independent of the assumption about crossed or nested occasions. Therefore, regarding distinguishability it should also be referred to Chapter 7.2.1.2.

still exists while including the control variables. Hence, hypothesis $H1c$ regarding the different vulnerability of job insecurity across gender is confirmed by the estimation results of the two-level Full APIM.

(b) Crossover Hypotheses

Regarding negative crossover of job insecurity to the mental health status for women (gender = 0) and hence hypothesis $H2a$, the relevant coefficient of the variable measuring partner's job insecurity is still negatively related to the mental health status in the two-level Full APIM (men's partner effect). A woman in a relationship with a man who suffers from job insecurity on average displays a lower mental health status by about 0.67 points (about 6.70% of a standard deviation), than a woman in a relationship with a man who does not suffer from job insecurity. The partner effect from men to women is therefore just slightly lower than in the two-level Base APIM, not including the control variables. Furthermore, the effect is still significant at a 1%-level of significance. Hence, hypothesis $H2a$ regarding crossover of men's job insecurity to women's mental health status can be confirmed.

Considering hypothesis $H2b$ and hence the negative crossover of women's job insecurity to men's mental health status (women's partner effect), the sum of the coefficients of the dummy variable measuring job insecurity of the partner and the corresponding interaction term with gender (Job Insec. Partner#Gender) has to be considered. If a man is in a relationship with a woman, suffering from job insecurity, his mental health status is on average about 0.43 points lower than the mental health status of a man in a relationship with a woman who does not experience job insecurity ($-0.6741 + 0.2477$). This effect corresponds to a decrease of about 4.30% of a standard deviation of the mental health status. Women's partner effect is therefore slightly lower by about 0.02 points in the two-level Full APIM than in the two-level Base APIM. The F-Test of joint significance for the variable, measuring partner's job insecurity and the corresponding interaction term (Job Insec. Partner#Gender), demonstrates a significance of women's parter effect at the 1%-level of significance in the two-level Full APIM (F(PJI;PJI#Gender)).

In the following, the effect sizes of women's and men's partner effects are additionally considered to examine hypothesis $H2c$, which assumes different vulnerability of job insecurity across gender to the disadvantage of men. A comparison of the coefficients displays that the partner effect from men to women is still more negative than the partner effect from women to men by about 0.25 points. Hypothesis $H2c$ is confirmed, even when including the control variables into the Over-time Standard APIM.

(c) Further Results

Being men is on average related to a better mental health status by about 1.90 points (about 19% of a standard deviation of the mental health status). In the two-level Base APIM this effect is stronger by about 0.26 points than in the two-level Full APIM. Contrary to the results of the two-level Base APIM, the continuous variable measuring time displays a significant effect in the Full APIM. Regarding the included control variables, a significant coefficient can be found for the variable measuring individual age. One additional year increases the mental health status on average by about 0.08 points. The effect is significant at the 1% level of significance. If an individual spends an additional year in education, the mental health status of this individual increases on average by about 0.05 points. This corresponds to an increase of the mental health status by about 0.50% of a standard deviation of the mental health status. However, the relation between education and the mental health status is not significant. Regarding the dummy variables, controlling for different occupation groups, two of the occupation dummy variables are found to be significant. If an individual works as a professional, the mental health status of this individual is on average about 0.66 points lower than the mental health status of an individual who is working in an elementary occupation. Additionally, also clerks on average have a lower mental health status than individuals in elementary occupations by about 0.55 points. The levels of significance thereby amount to 5%, respectively 10%. The occupation dummy variable controlling for the occupation group of legislators, senior officials and managers as well as the variable controlling for the occupation group of technicians and associate professionals are negatively related to the mental health status. Working as service workers, shop sales workers or market sales workers is on average positively related to the mental health status compared to working in elementary occupations. This is also true for the occupation group of skilled agricultural workers, fishery workers, craft workers and trade workers as well as for plant operators, machine operators and assemblers. However, the relationships between these occupation dummy variables and the mental health status are not significant.

(d) Distribution of Variance and Goodness of Fit

The distribution of the total variance of the mental health status into level-1 and level-2 variance is very similar to the one in the two-level Base APIM. For women, the proportion of variance due to differences between individuals amounts to about 57% $((55.3523/(55.3523 + 42.3688)) * 100)$ and the proportion of variance due to differences between dyads amounts to about

43% ((42.3688/(55.3523+42.3688))∗100). Considering male individuals, 64% ((55.3523/(55.3523+30.8520))∗100) of the total variance is due to differences between individuals and 36% ((30.8520/(55.3523+30.8520))∗100) goes back to differences between dyads. Regarding the relative model fit indices, the AIC displays a value of 224,880.2 for the two-level Full APIM. The BIC value amounts to 225,105.7 and the -2LL value amounts to 224,826.2. Comparing these relative model fit indices with those of the two-level Base APIM, it can be seen that the AIC and the BIC as well as the -2LL value of the two-level Full APIM display lower values than those of the two-level Base APIM. This indicates that the two-level Full APIM fits the underlying data better than the two-level Base APIM. To determine if this difference between the model fits is even significant, the results of a likelihood-ratio test, assuming that the two-level Base APIM fits the data significantly better ($H0$), are presented in Table 19. It is displayed that the null hypotheses $H0$ can be rejected. Hence, the two-level Full APIM including the variables age, education and the occupation dummy variables fits the data significantly better than the two-level Base APIM without control variables.[102]

Table 19: Likelihood-Ratio Test – Two-Level Base APIM vs. Two-Level Full APIM

Likelihood-Ratio Test	LR chi2(9) = 102.08
(Assumption: Base APIM nested in Full APIM)	Prob>chi2 = 0.0000

7.2.2.2 Robustness Checks

After presenting the result of the two-level Base APIM and the two-level Full APIM, some robustness checks will be additionally conducted to approach a causal interpretation between job insecurity, partner's job insecurity and the mental health status in the two-level Over-time Standard APIM. In order to be able to compare the results, the process will be the same as for the three-level Over-time Standard APIM before. It is again referred to the four necessary conditions which have to be fulfilled for a causal interpretation between two variables by Kube (1991); Hildebrandt et al. (1992); Haenecke (2002); Herrmann et al. (2008); Trommsdorff and Teichert (2011); Döring and

[102] The residual diagnostic of the two-level Full APIM shows, that the residuals at each level have a mean of 0 and are normally distributed. Furthermore, the residuals are determined to be uncorrelated with the independent variables. A test of linearity of the relationship between job insecurity and mental health does again not have to be conducted as job insecurity is included as a dummy variable in the two-level Full APIM.

Bortz (2016). To fulfill the condition requiring that a temporal chronology between both variables exists and the condition that requires that effects due to additional variables have to be excluded, temporal asymmetry and unobserved heterogeneity respectively omitted variable bias are considered. Thereby, temporal asymmetry is examined by estimating a two-level Over-time Standard APIM including $t-1$ lag variables of the independent variables job insecurity and partner's job insecurity. Hereinafter, this model is referred to as two-level Lag Model. The exclusion of effects due to additional variables and hence unobserved heterogeneity and omitted variable bias is examined by considering a two-level Hybrid Model.

Two-Level Lag Model

Table 20 represents the results of a two-level Lag Model with the lagged independent variables job insecurity and partner's job insecurity. The dependent variable, the mental health status, is still measured in time t and hence at the years 2002, 2004, 2006, 2008, 2010 and 2012. Job insecurity and partner's job insecurity however are measured at time $t-1$ and hence in the corresponding years 2001, 2003, 2005, 2007, 2009 and 2011. While including lag variables, the number of observations is reduced by about 20%, because not all individuals are observed in each of the examined years. Nevertheless, 25,118 individual-year observations, 10,294 individuals and a number of 5,147 dyads remain. In the two-level Lag Model it is also controlled for age, education and the occupation dummy variables based on the ISCO.

(a) Spillover Hypotheses

Considering hypothesis $H1a$ and hence the negative spillover of job insecurity to the mental health status for women (gender $= 0$), the coefficient of the variable measuring job insecurity in $t-1$ is still displayed to be negative (women's actor effect). If a woman suffers from job insecurity in $t-1$, the mental health status of this woman in t is on average by about 1.08 points lower (about 10.80% of a standard deviation), than the mental health status of a woman who does not suffer from job insecurity in $t-1$. The effect is estimated to be significant at the 1%-level of significance. This confirms the negative spillover of women's job insecurity to women's mental health status. Hypothesis $H1a$ can be confirmed, when job insecurity in $t-1$ is included into the model.

Table 20: Two-Level Lag Model

	Two-Level $t-1$ Lag Model
Constant	49.9720***
	(0.3444)
Gender	1.9351***
	(0.2055)
Job Insecurity in t-1	-1.0786***
	(0.1840)
Partner Job Insecurity in t-1	-0.3788**
	(0.1853)
Job Insec. t-1#Gender	-0.8196***
	(0.2554)
Job Insec. t-1 Partner#Gender	0.2370
	(0.2550)
Time	-0.0720*
	(0.0375)
Age	0.0832***
	(0.0102)
Yrs in Education	0.0661*
	(0.0386)
Legislators/Senior Officials/Managers	0.1613
	(0.3782)
Professionals	-0.4410
	(0.3544)
Techn./Assoc. Profess.	-0.0604
	(0.3104)
Clerks	-0.3260
	(0.3366)
Service/Sales Workers	0.3745
	(0.3426)
Agric./Fishery/Craft/Trade Workers	0.0209
	(0.3283)
Plant/Machine Operators/Assemblers	0.5599
	(0.3722)

Table 20 (continued): Two-Level Lag Model

Level 2 Variance - Women	44.8926***
	(0.9170)
Level 2 Variance - Men	35.0516***
	(0.8305)
Level 1 Variance	54.8874***
	(0.4277)
F(JI_{t-1};JI_{t-1}#Gender)	138.19***
F(PJI_{t-1};PJI_{t-1}#Gender)	4.80*
AIC	180461.7
BIC	180687.2
-2 Log likelihood	180407.8
Number of Observations	25,118
Number of Individuals	10,294
Number of Dyads	5,147

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Dependent variable: MCS in t. Estimation procedure: ML. Base category for Gender: Men. Base category for occupation dummy variables: Elementary occupations.

To examine hypothesis $H1b$ and hence the negative spillover of job insecurity in $t-1$ to the mental health status for men (gender = 1) in t, the variable measuring job insecurity in $t-1$ and the corresponding interaction term with gender (Job Insec. t-1#Gender) have to be considered. If a man experienced job insecurity in $t-1$, the mental health status of this man in t is on average even by about additional 0.82 points lower than for a man who does not experience job insecurity in $t-1$ ($-1.0786+(-0.8196)=-1.8982$ points). Therefore, the mental health status of men who suffer from job insecurity in $t-1$ decreases by about 1.90% points and hence by about 19.00% of a standard deviation (men's actor effect). The significance of the interaction between job insecurity and gender (Job Insec. in t-1#Gender) is determined using an F-Test of joint significance of the variable measuring job insecurity and the corresponding interaction term. The result displays a significance of men's actor effect at the 1%-level of significance ($F(JI_{t-1}, JI_{t-1}\#Gender)$. Therefore, hypothesis $H1b$ can be confirmed, when job insecurity in $t-1$ is included in the model.

The effect sizes of women's and men's actor effects are considered in the following to examine hypothesis $H1c$ and hence the different vulnerability of job insecurity for women and men. The actor effect of job insecurity in $t-1$ displays a more negative coefficient for men than for women. As both effects

are significant, the results are in line with hypothesis $H1c$ and confirm the different vulnerability of job insecurity for women and men in the two-level Lag Model.

(b) Crossover Hypotheses

Hypothesis $H2a$ deals with the negative crossover of men's job insecurity in $t-1$ to women's mental health status in t (men's partner effect) and is therefore examined for women (gender = 0) under the consideration of the variable, measuring partner's job insecurity in $t-1$. The partner effect from men's job insecurity in $t-1$ on women's mental health status in t amounts to about -0.38 points. If a woman is in a relationship with a partner who suffers from job insecurity in $t-1$, the mental health status of this women at time t is on average by about 0.38 points (about 3.80% of a standard deviation) worse than the mental health status of a woman in a relationship with a partner who suffers from job insecurity in $t-1$. Thereby, the estimated coefficient of the variable measuring if a partner suffers from job insecurity in $t-1$, is significant at a 5% level of significance. Hypothesis $H2a$ is confirmed by the results of the two-level Lag Model.

With respect to hypothesis $H2b$ and hence the negative crossover of women's job insecurity in $t-1$ to men's mental health status in t (women's partner effect), the variable measuring partner's job insecurity in $t-1$ and the corresponding interaction term with gender (Job Insec. Partner#Gender) have to be considered. The sum of both coefficients displays that the mental health status of a man at time t, in a relationship with a woman who experiences job insecurity in $t-1$, is on average by about 0.14 points $(-0.3788+0.2370)$ lower, than for a man in a relationship with a woman who does not experience job insecurity in $t-1$. This effect corresponds to about 1.40% of a standard deviation of the mental health status. The joint significance of job insecurity in $t-1$ and the corresponding interaction of this variable with gender (Job Insec. Partner#Gender) is determined by an F-Test of which the result is displayed in the lower part of Table 20 (F(PJI_{t-1};PJI_{t-1}#Gender)). The result displays a significance at the 10%-level. Hence, women's partner effect of job insecurity in $t-1$ is significantly related to men's mental health status in t and hypothesis $H2b$ can be confirmed, even when lag variables of women's job insecurity are considered.

To examine the different vulnerability for women and men with regard to crossover of job insecurity and hence hypothesis $H2c$, the effect sizes of women's and men's partner effects are considered. The partner effect from women to

men is about 0.24 points less negative, than the partner effect from men to women. Hence, hypothesis $H2c$ can be confirmed, considering partner's job insecurity in $t-1$. Negative crossover of job insecurity to the mental health status is more harmful if men experience job insecurity than if women do.

(c) Further Results

The two-level Lag Model estimates a larger effect size of gender by about 0.04 points, compared to the two-level Full APIM above. Being male increases the mental health status on average by about 1.94 points, which corresponds to an increase by about 19.40% of a standard deviation of the mental health status when temporal asymmetry is considered. Thereby, the effect of gender still remains significant. This also applies to the variable representing time. The coefficient of this variable, included to capture time trends, is still significant in the two-level Lag Model. An additional year of age also displays a larger effect size in the two-level Lag Model than in the two-level Full APIM. The significance of age however remains at a 1%-level of significance. If an individual gets older by one additional year, the mental health status increases on average by about 0.08 points (about 0.80% of a standard deviation of the mental health status). Hence, the estimated effect size of the two-level Lag Model regarding the variable age deviates only slightly compared to the estimation result in the two-level Full APIM. The deviation is only visible at the third decimal place. The variable which measures the years an individual spends in education however deviates in the two-level Lag Model in terms of significance and effect size from those of the two-level Full APIM. One additional year of education is displayed to be significantly related to an increased mental health status by about 0.06 points, according to 0.60% of a standard deviation of the mental health status. The relationship is significant at the 10%-level in the two-level Lag Model. The estimation results of the dummy variables, controlling for the different occupation groups based on the ISCO, display no significant coefficients once temporal asymmetry is modeled through a two-level Lag Model. Furthermore, the coefficient sign as well as the effect size of the dummy variable, which measures if an individual is working in the occupation group of legislators, senior officials and managers, changes. For all the other occupation dummy variables, the coefficient signs remain the same, but also the effect sizes change. For the occupation groups of legislators, senior officials and managers as well as for the occupation group of service workers, shop sales workers and market sales workers the effect size is increased once it is checked for temporal asymmetry. The same is true for the occupation group of plant operators, machine operators and assemblers. However, the

effect sizes of the remaining occupation dummy variables display lower effect sizes in the two-level Lag Model than in the two-level Full APIM.

(d) Goodness of Fit and Closing Summary

The relative model fit indices of the two-level Lag Model could be found in the lower part of Table 20. The AIC value amounts to 180,461.7, the BIC value amounts to 180,687.2 and finally, the -2LL value amounts to 180,407.8. Compared to the corresponding values of the two-level Full APIM, the relative model fit indices display lower values for the two-level Lag Model, indicating a better model fit for the two-level Lag Model than for the two-level Full APIM. Using a likelihood-ratio test, it can not be tested if the difference between the model fit indices is significant. The assumption of the likelihood-ratio test, that one of the models has to be an extension of the other one, is not fulfilled in the present case.[103] In summary, the results of the two-level Lag Model are in line with the assumed hypotheses. The negative spillover hypotheses and the negative crossover hypotheses of job insecurity to the mental health status are supported for women and for men. Additionally, the assumed different vulnerability of spillover and crossover of job insecurity for women and men can be confirmed under the consideration of temporal asymmetry.

Two-level Hybrid Model

The following robustness check refers to the exclusion of effects due to additional variables. A two-level Hybrid Model of job insecurity and the mental health status is therefore estimated. To do so, the time-varying independent variables of interest, job insecurity and partner's job insecurity, are differentiated in the within-individual parts and the between-individual parts of the variables. The within-individual parts of the variables represent the changes between a situation of experiencing *no job insecurity* and a situation of experiencing *job insecurity*, respectively for *partner's job insecurity* within each individual. The between-individual part however displays the average value of the variable measuring job insecurity respectively partner's job insecurity of each individual and the variation of this average value between the individuals (Krause and Urban, 2013). The separation into the within-individual part and the between-individual part of the time-varying variables enables to control for unobserved heterogeneity and omitted variable bias (Krause and Urban, 2013).

The results of the two-level Hybrid Model are represented in Table 21. The within-individual parts of the variables, measuring job insecurity respectively

[103] For more information see Snijders and Bosker (2012).

partner's job insecurity, are represented by the variable Δ *Job Insecurity* and the variable Δ *Job Insecurity Partner*. Because the within-individual parts of job insecurity and partner's job insecurity can be interpreted as the change from the status of *no job insecurity* to the status of *job insecurity*, the within-individual parts can be used to verify the assumed hypotheses. As 11,769 observations go back to individuals who change between the status of *no job insecurity* and the status of *job insecurity*, the within-individual effect of job insecurity is estimated using 11,769 observations which equals to about 38% of the used individual-year observations. These observations comprise 2,295 dyads.

The between-individual parts of the variables measuring job insecurity respectively partner's job insecurity are represented by *Job Insecurity_Mean* respectively *Job Insecurity Partner_Mean*. For a content-related interpretation, the between-individual parts of the variables are not of further interest. Nevertheless, the estimations of these variables can be used as references for the within-individual parts of the regarding variables to identify the presence of unobserved heterogeneity (Krause and Urban, 2013). When the actor and partner effects of women and men from the two-level Hybrid Model are compared with those of the two-level Full APIM, it has to be taken into consideration, that the Hybrid Model does not estimate the general effect of job insecurity, but the within-individual part of job insecurity. Nevertheless, a comparison should be conducted, to enable an understanding of the deviations.

(a) Spillover Hypotheses

Regarding the negative spillover of job insecurity to the mental health status for women (gender = 0) and hence hypothesis $H1a$, the estimation results in Table 17 show that the within-individual part of women's job insecurity Δ *Job Insecurity* is negatively related to women's mental health status (women's actor effect). The results of Table 21 display, that if a woman changes from a situation of *no job insecurity* to a situation of *job insecurity*, the mental health status of this woman decreases on average by about 0.96 points. This corresponds to a decrease by about 9.60% of a standard deviation of the mental health status. Because the effect is significant at the 1%-level of significance, hypothesis $H1a$ and hence a worse mental health status for women who suffer from job insecurity compared to women who do not suffer from job insecurity can be confirmed by the two-level Hybrid Model.

Table 21: Two-Level Hybrid Model

	Two-Level Hybrid Model
Constant	52.0352***
	(0.3147)
Gender	1.7281***
	(0.1350)
Job Insecurity_Mean	-3.9741***
	(0.2340)
Job Insecurity Partner_Mean	-0.6893***
	(0.2326)
Δ Job Insecurity	-0.9577***
	(0.2084)
Δ Job Insecurity Partner	-0.4990**
	(0.1942)
Δ Job Insec.#Gender	-0.3325
	(0.2959)
Δ Job Insec. Partner#Gender	0.3121
	(0.2278)
Time	-0.0785**
	(0.0325)
Age	0.0719***
	(0.0087)
Yrs in Education	0.0161
	(0.0341)
Legislators/Senior Officials/Managers	-0.1640
	(0.3318)
Professionals	-0.8030***
	(0.3106)
Techn./Assoc. Profess.	-0.3539
	(0.2721)
Clerks	-0.6117**
	(0.2951)
Service/Sales Workers	0.1965
	(0.3011)
Agric./Fishery/Craft/Trade Workers	0.0801
	(0.2870)
Plant/Machine Operators/Assemblers	0.4552
	(0.3278)

Table 21 (continued): Two-Level Hybrid Model

Level 2 Variance - Women	44.6300***
	(0.7281)
Level 2 Variance - Men	34.5533***
	(0.6364)
Level 1 Variance	55.5640***
	(0.3948)
F(ΔJI;ΔJI#Gender)	54.18***
F(ΔPJI;ΔPJI#Gender)	6.67**
AIC	224790.9
BIC	225016.4
-2 Log likelihood	224736.8
Number of Observations	31,316
Number of Individuals	12,826
Number of Dyads	6,376

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Dependent variable: MCS. Estimation procedure: ML. Base category for Gender: Men. Base category for occupation dummy variables: Elementary occupations.

To examine the negative spillover of job insecurity for men (gender = 1) assumed by hypothesis $H1b$, the sum of the variable Δ *Job Insecurity* and the interaction of Δ *Job Insecurity* and gender (Δ Job Insec.#Gender) has to be considered. The sum of the coefficients of these variables shows that if a man changes from a situation in which he is not suffering from job insecurity to a situation in which he is suffering from job insecurity, his mental health status decreases on average even by about 1.29 points $(-0.9577 + (-0.3325))$. This corresponds to a decrease of about 12.90% of a standard deviation of the mental health status (men's actor effect). Thereby, the significance of the effect is determined using an F-Test of joint significance. The result is displayed in the lower part of Table 21 (F(ΔJI;ΔJI#Gender)) and displays a significance at the 1%-level. Hypothesis $H1b$ can therefore be confirmed, even when it is controlled for unobserved heterogeneity and omitted variable bias.

Looking furthermore at the effect sizes of the significant actor effects of women and men to examine hypothesis $H1c$, which refers to the different vulnerability of job insecurity for women and men, it can be seen that men's actor effect displays a more negative effect size than women's actor effect by about 0.33 points. Hence, hypothesis $H1c$ considering different vulnerability of women and men can additionally be confirmed by the two-level Hybrid Model.

(b) Crossover Hypotheses

Hypothesis $H2a$ and thus the negative crossover of men's job insecurity to women's mental health status is additionally confirmed by the results of the two-level Hybrid Model. If a woman changes from a situation in which she is in a relationship with a man who does not suffer from job insecurity to a situation in which she is in a relationship with a man who suffers from job insecurity, the mental health status of this woman decreases on average by about 0.50 points (men's partner effect). This equals to a decrease in the mental health status by about 5.00% of a standard deviation, displayed by the variable measuring partner's job insecurity in Table 21. The coefficient of the variable measuring the within-individual part of partner's job insecurity is significant at the 5%-level of significance and hypothesis $H2a$ can be confirmed.

To examine hypothesis $H2b$ and hence women's partner effect, the sum of the coefficients of the variable measuring a change from a relationship with a partner who does not suffer from job insecurity to a relationship with a partner who suffers from job insecurity and the associated interaction term of this variable with gender (Δ Job Insec. Partner#Gender) has to be regarded. If a man changes from a situation in which he is in a relationship with a woman who does not suffer from job insecurity to a situation in which he is in a relationship with a woman who suffers from job insecurity, the mental health status of this man decreases on average by about 0.19 points ($-0.4990 + 0.3121$). This corresponds to a decrease in the mental health status by about 1.90% of a standard deviation. The F-Test of joint significance of the within-individual part of partner's job insecurity and the corresponding interaction term with gender (Δ Job Insec. Partner#Gender) displays a significant relation at the 5%-level (F(ΔPJI;ΔPJI#Gender)). Therefore, the negative crossover hypothesis, $H2b$, of job insecurity to the mental health status for men is confirmed, while it is controlled for unobserved heterogeneity and omitted variable bias.

Regarding the effect sizes to examine different vulnerability of partner's job insecurity and hence hypothesis $H2c$, it can be seen that the relationship between men's change from *no job insecurity* to *job insecurity* and the mental health status of his female partner is stronger than the relationship between women's change from *no job insecurity* to *job insecurity* and the mental health status of her male partner. Hypothesis $H2c$ and hence the different vulnerability of crossover of job insecurity for women and men is confirmed by the two-level Hybrid Model, controlling for unobserved heterogeneity and omitted variable bias.

(c) Further Results

The other independent variable measuring gender is estimated with a coefficient of about 1.73. This represents a lower effect size, while it is controlled for unobserved heterogeneity and omitted variables in the two-level Hybrid Model, compared to the two-level Full APIM. Significance and coefficient signs however remain the same. The variable representing time is still significant in the two-level Hybrid Model. Regarding the included control variables, individual age is estimated with a slightly lower effect size in the two-level Hybrid Model compared to the two-level Full APIM. However, the effect is still determined to be significant at the 1%-level. One additional year an individual spends in education is related to an increased mental health status by about 0.02 points, but the effect is still not significant in the two-level Hybrid Model. Regarding the occupation dummy variables, it can be seen that the coefficient signs stay the same compared to the two-level Full APIM. The effect sizes as well as the levels of significance however change. The dummy variable, controlling for the occupation group of professionals as well as the one controlling for the occupation group of clerks are still significant while it is controlled for unobserved heterogeneity and omitted variable bias. The levels of significance of those coefficients have changed. The significance of the effect of belonging to the occupation group of professionals increases from a 5%-level to a 1%-level of significance. For the occupation group of clerks, the level of significance increases from the 10%-level to the 5%-level of significance. Working as a professional or as a clerk decreases the mental health status on average by about 0.80 respectively 0.61 which correspond to a decrease of about 8.00%, respectively 6.10% of a standard deviation of the mental health status.

(d) Goodness of Fit and Closing Summary

Looking at the relative model fit indices in the lower part of Table 21, the AIC displays a value of 224790.9, the BIC a value of 225016.4 and the -2LL displays a value of 224736.8. Compared to the values of the relative model fit indices of the two-level Full APIM, it can be seen that the AIC, the BIC and the -2LL display lower values for the two-level Hybrid Model than for the two-level Full APIM. This indicates that controlling for unobserved heterogeneity and omitted variables improves the model fit. Additionally, the significant differences between the within-individual and the between-individual parts of the independent variables job insecurity and partner's job insecurity are a tribute to the existence of unobserved heterogeneity in the underlying data. Comprehensively, when it is controlled for unobserved heterogeneity and omitted variables, all assumed hypotheses regarding spillover and crossover of job insecurity to

the mental health status are still confirmed for female and male individuals. Furthermore, the different vulnerability of job insecurity for women and men is displayed by the results of the two-level Hybrid-Model.

7.3 Model Comparison

To compare the results of the three-level Over-time Standard APIM and the two-level Over-time Standard APIM, Table 22 represents the results of both Full APIMs next to each other. The two-level Full APIM is presented in column 1. The three-level Full APIM is presented in column 2. In the direct comparison of both models, it can be seen that most of the coefficients display very similar results. Regarding the significance of the coefficients, all coefficients that display significant effects in the two-level Full APIM also do so in the three-level Full APIM. The levels of significance additionally stay the same. Comparing the effect sizes of the variables, in 62.50% of the cases the estimation of the two-level Full APIM displays a larger effect size for a corresponding variable than the three-level Full APIM. Only the estimation of six variables out of sixteen explanatory variables displays larger effect sizes in the three-level Full APIM than in the two-level Full APIM.

Considering the independent variables measuring job insecurity and partner's job insecurity as well as the corresponding interaction terms, it can be seen that in both models all four effects are highly significant at the 1%-level. Regarding the effect size of the coefficients, the variable measuring job insecurity (women's actor effect) only differs by 0.0048 points, whereas the effect size in the two-level Full APIM is found to be larger. The interaction term of job insecurity and gender (men's actor effect) however differs by 0.1555 points and represents the strongest deviation considering the estimation results of the two-level Full APIM and the three-level Full APIM. The effect size of the interaction term is found to be larger in the two-level than in the three-level Full APIM. The estimation of the coefficient of the variable measuring partner's job insecurity (men's partner effect) presents a larger effect by 0.0361 in the two-level than in the three-level Full APIM. The estimation of the corresponding interaction effect (women's partner effect) however displays a larger effect size in the three-level Full APIM although the difference only amounts to 0.0072 points. The estimation of the variable measuring gender is again found to be larger in the two-level than in the three-level Full APIM. The difference amounts to 0.0767 points. The level of significance of the variable representing time, remains at the 1%-level of significance in the two-level Full APIM as well as in the three-level Full APIM.

Table 22: Two-Level Model vs. Three-Level Model – Full APIMs

	(1) Two-Level Full APIM	(2) Three-Level Full APIM
Constant	50.9825***	50.9166***
	(0.3039)	(0.3027)
Gender	1.8993***	1.8226***
	(0.1846)	(0.1866)
Job Insecurity	-1.8806***	-1.8758***
	(0.1648)	(0.1589)
Job Insecurity Partner	-0.6741***	-0.6379***
	(0.1675)	(0.1625)
Job Insec.#Gender	-0.6543***	-0.4988**
	(0.2288)	(0.2288)
Job Insec. Partner#Gender	0.2477	0.2549
	(0.2276)	(0.2285)
Time	-0.0991***	-0.0999***
	(0.0324)	(0.0326)
Age	0.0790***	0.0783***
	(0.0086)	(0.0087)
Yrs in Education	0.0476	0.0491
	(0.0339)	(0.0343)
Legislators/Senior Officials/Managers	-0.0917	-0.0935
	(0.3321)	(0.3341)
Professionals	-0.6631**	-0.6157**
	(0.3105)	(0.3115)
Techn./Assoc. Profess.	-0.2605	-0.2283
	(0.2725)	(0.2720)
Clerks	-0.5549*	-0.5309*
	(0.2957)	(0.2946)
Service/Sales Workers	0.2767	0.3363
	(0.3018)	(0.2999)
Agric./Fishery/Craft/Trade Workers	0.0643	0.0550
	(0.2883)	(0.2903)
Plant/Machine Operators/Assemblers	0.4081	0.4110
	(0.3294)	(0.3317)

Table 22 (continued): Two-Level Model vs. Three-Level Model – Full APIMs

Level 3 Variance		25.7156***
		(0.4795)
Level 2 Variance		14.8617***
		(0.4432)
Women	42.3688***	
	(0.8112)	
Men	30.8520***	
	(0.7442)	
Level 1 Variance	55.3523***	56.3997***
	(0.3810)	(0.3730)
F(JI;JI#Gender)	346.67***	352.51***
F(PJI;PJI#Gender)	22.98***	21.38***
AIC	224880.2	224955.3
BIC	225105.7	225122.4
-2 Log likelihood	224826.2	224915.4
Number of Observations	31,316	31,316
Number of Individuals	12,826	12,826
Number of Dyads	6,376	6,376

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Dependent variable: MCS. Estimation procedure: ML. Base category for Gender: Men. Base category for occupation dummy variables: Elementary occupations.

Regarding the control variables, the largest deviation between the estimations can be found for the occupation dummy variable that measures if an individual works in the occupation group of service workers, shop sales workers and market sales workers. The deviation amounts to 0.0596, whereas the larger effect size is displayed in the three-level Full APIM. The variable controlling for age displays a slightly lower coefficient of 0.0007 points in the three-level than in the two-level Full APIM. The estimation's deviation of the occupation dummy variable measuring if an individual is working as a clerk amounts to 0.0240 points. The larger effect size is displayed in the two-level Full APIM. The coefficient of the variable measuring if an individual belongs to the occupation group of professionals presents a deviation in the estimated effect size of 0.0474 points. The larger effect size for professionals is found in the two-level Full APIM. The deviations of the insignificant control variables range between 0.0015 points regarding years of education and 0.0322 points considering the occupation group of technicians and associate professionals.

Since the variances at the different levels are differentiated between women and men in the two-level Full APIM, but not in the three-level Full APIM, the

estimations cannot be compared directly. However, it is possible to compare the models based on the relative model fit indices displayed in the lower part of Table 22. The AIC, the BIC and the -2LL display lower values for the two-level Full APIM than for the three-level Full APIM, indicating that the two-level Full APIM fits the underlying data better than the three-level Full APIM.

To determine if the two-level Full APIM fits the data even significantly better than the three-level Full APIM, a likelihood-ratio test is performed. The results are displayed in Table 23. The likelihood-ratio test verifies the null hypothesis $H0$ that the three-level Full APIM fits the data significantly better than the two-level Full APIM. This is due to the fact that the three-level Full APIM is, regardless of its three-levels, not the most restrictive one. Because of the additional dummy variables female and male, which are included in the two-level Full APIM, the two-level Full APIM holds a higher number of degrees of freedom. Hence, the two-level Full APIM is the more complex model. The results display that the null hypothesis $H0$ can be rejected. The three-level model does not fit the data significantly better than the two-level model. Therefore, the relative model fit indices display a better model fit for the two-level Full APIM than for the three-level Full APIM, and the likelihood-ratio test indicates no significant better model fit of the three-level Full APIM.

Table 23: Likelihood-Ratio Test – Three-Level APIM vs. Two-Level APIM

Likelihood-Ratio Test	LR chi2(7) = 89.12
(Assumption: 2-Level nested in 3-Level APIM)	Prob>chi2 = 0.0000

Two-Level and Three-Level Lag Models

The results of the two-level Lag Model and the three-level Lag Model, including the lag independent variables of job insecurity and partner's job insecurity $t-1$, as well as the control variables are presented in Table 24. Column 1 displays the results of the two-level Lag Model, column 2 however shows the results of the three-level Lag Model. Very similar to the results of the comparison of the Full APIMs above, the estimated coefficients of the Lag Models show that in 75% of the cases the two-level Lag Model estimates a larger effect size than the three-level Lag Model. Only four variables display an effect size with a higher value in the three-level model than in the two-level model. The coefficient of the interaction term between partner's job insecurity in $t-1$ and gender as well as the coefficient of the variable *time* display a

lower effect size in the two-level Lag Model than in the three-level Lag Model. Furthermore, the occupation dummy variables, controlling for the occupation group of technicians and associate professionals as well as for the occupation group of service workers, shop sales workers and market sales workers, display lower effect sizes in the two-level Lag Model than in the three-level Lag Model.

Regarding the estimated significances, the results mostly remain the same. Except for the level of significance of the interaction term between partner's job insecurity in $t-1$ and gender (F(PJI_{t-1};PJI_{t-1}#Gender)). Here, the significance at the 10%-level estimated in the two-level model disappears, once the data is modeled using a three-level Lag Model. In the two-level Lag Model the estimated coefficient of the variable measuring job insecurity in $t-1$ (women's actor effect) is 0.0173 points above the coefficient estimated in the three-level model. A very similar deviation of 0.0180 points can be found for the variable measuring if a partner suffers from job insecurity in $t-1$ (men's partner effect). Thereby, the deviation is again represented by a larger effect size in the two-level Lag Model. The coefficient of the interaction effect between job insecurity and gender (men's actor effect) displays a larger effect size in the two-level Lag Model, as well. The deviation amounts to 0.1379 points. The coefficient of the interaction effect between partner's job insecurity and gender (women's partner effect) however displays a stronger effect in the three-level Lag Model with a deviation of 0.0325 points. Summarized, it is found that men's actor effect displays the strongest deviation between the estimation results of the two-level Lag Model and those of the three-level Lag Model.

The variable measuring gender still displays a significant effect, which deviates in effects size by 0.0926. The higher effect size is estimated by the two-level Lag Model. The variable representing the years of observations deviates in the level of significance. In the two-level Lag Model, the effect is significant at the 10%-level, whereas the level of significance in the three-level Lag model amounts to 5%. The smallest deviation between the estimation result of the control variables of the two-level Lag Model and of the three-level Lag Model is found for the years an individual spends in education. Here, the deviation only amounts to 0.0002 points. The differences between the effect sizes of the remaining control variables rank between 0.0007 points for the variable age and 0.0415 points considering the occupation group of service workers, shop sales workers and market sales workers.

Table 24: Two-Level Model vs. Three-Level Model – Lag Models

	(1) Two-Level Lag Model	(2) Three-Level Lag Model
Constant	49.9720***	49.9426***
	(0.3444)	(0.3427)
Gender	1.9351***	1.8425***
	(0.2055)	(0.2068)
Job Insecurity in t-1	-1.0786***	-1.0613***
	(0.1840)	(0.1783)
Partner Job Insecurity in t-1	-0.3788**	-0.3608**
	(0.1853)	(0.1807)
Job Insec. t-1#Gender	-0.8196***	-0.6817***
	(0.2554)	(0.2557)
Job Insec. t-1 Partner#Gender	0.2370	0.2695
	(0.2550)	(0.2555)
Time	-0.0720*	-0.0738**
	(0.0375)	(0.0376)
Age	0.0832***	0.0825***
	(0.0102)	(0.0103)
Yrs in Education	0.0661*	0.0659*
	(0.0386)	(0.0389)
Legislators/Senior Officials/Managers	0.1613	0.1447
	(0.3782)	(0.3801)
Professionals	-0.4410	-0.4154
	(0.3544)	(0.3551)
Techn./Assoc. Profess.	-0.0604	-0.0646
	(0.3104)	(0.3097)
Clerks	-0.3260	-0.3221
	(0.3366)	(0.3352)
Service/Sales Workers	0.3745	0.4160
	(0.3426)	(0.3406)
Agric./Fishery/Craft/Trade Workers	0.0209	0.0019
	(0.3283)	(0.3302)
Plant/Machine Operators/Assemblers	0.5599	0.5437
	(0.3722)	(0.3747)

Table 24 (continued): Two-Level Model vs. Three-Level Model – Lag Models

Level 3 Variance		27.2299***
		(0.5494)
Level 2 Variance		15.3994***
		(0.4992)
Women	44.8926***	
	(0.9170)	
Men	35.0516***	
	(0.8305)	
Level 1 Variance	54.8874***	55.5274***
	(0.4277)	(0.4153)
F(JI_{t-1};JI_{t-1}#Gender)	138.19***	128.38***
F(PJI_{t-1};PJI_{t-1}#Gender)	4.80*	4.27
AIC	180461.7	180488.7
BIC	180687.2	180651.3
-2 Log likelihood	180407.8	180448.8
Number of Observations	25,118	25,118
Number of Individuals	10,294	10,294
Number of Dyads	5,147	5,147

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Dependent variable: MCS in t. Estimation procedure: ML. Base category for Gender: Men. Base category for occupation dummy variables: Elementary occupations.

The model fit indices represent a heterogeneous picture. The AIC and the -2LL display lower values for the two-level Lag Model with values of 180,461.7, respectively 180,407.8 than for the three-level Lag Model. The BIC however indicates a better model fit for the three-level Lag Model with a value of 180,651.3 than for the two-level Lag Model. The result of a likelihood-ratio test, testing the null hypothesis $H0$ that the three-level Lag Model fits the data significantly better than the two-level Lag Model is presented in Table 25. The results display that the null hypothesis $H0$ can be rejected. Following the likelihood-ratio test, the two-level Lag Model fits the underlying data significantly better than the three-level Lag Model.

Table 25: Likelihood-Ratio Test – Three-Level vs. Two-Level Lag Model

Likelihood-Ratio Test	LR chi2(7) = 40.97
(Assumption: 2-Level nested in 3-Level APIM)	Prob>chi2 = 0.0000

Two-Level and Three-Level Hybrid Models

To compare the results of the two-level Hybrid Model and the three-level Hybrid Model, where it is controlled for unobserved heterogeneity and omitted variable bias, Table 26 displays the results of both Hybrid Models next to each other. Column 1 presents the two-level Hybrid Model, column 2 however the three-level Hybrid Model. Regarding the estimated significances, it can be seen that all estimated coefficients, which are significant in the two-level Hybrid Model, are still significant in the three-level Hybrid Model. Except for the interaction between the within-individual part of the variable measuring partner's job insecurity and gender. Here, the level of significance changes from the 1%-level in the two-level model to a significance at the 5%-level in the three-level Hybrid Model. The effect sizes of seven variables are larger in the two-level Hybrid Model and the effect sizes of eleven variables are larger in the three-level Hybrid Model. Hence, 68.75% of the estimated coefficients display a larger effect size in the three-level Hybrid Model than in the two-level Hybrid Model.

Both variables measuring the between-individual parts, the between-individual part of job insecurity (Job Insecurity_Mean) and the between-individual part of partner's job insecurity (Job Insecurity Partner_Mean), display larger coefficients by 0.0171 points, respectively 0.0103 points in the two-level Hybrid Model than in the three-level Hybrid Model. The coefficient of the within-individual part of the variable measuring job insecurity (Δ Job Insecurity) as well as the associated interaction term with gender (Δ Job Insec.#Gender) is estimated with a larger effect size of 0.016 points (women's actor effect) respectively 0.0009 points (men's actor effect) in the two-level Hybrid Model than in the three-level Hybrid Model. Comparing the estimations of the coefficient of the within-individual part of the variable measuring partner's job insecurity (Δ Job Insec. Partner), the effect size in the two-level Hybrid Model is 0.0034 points above the estimation in the three-level Hybrid Model (men's partner effect). The related coefficient of the interaction term with gender (Δ Job Insec. Partner#Gender) in the two-level Hybrid Model also deviates slightly from the corresponding coefficient in the three-level Hybrid Model. Thereby, the coefficient displays a lower effect size of 0.0098 points in the two-level Hybrid Model (women's partner effect). Therefore, deviations are rather small.

Table 26: Two-Level Model vs. Three-Level Model – Hybrid Models

	(1) Two-Level Hybrid Model	(2) Three-Level Hybrid Model
Constant	52.0352***	52.0108***
	(0.3147)	(0.3132)
Gender	1.7281***	1.7307***
	(0.1350)	(0.1353)
Job Insecurity_Mean	-3.9741***	-3.9570***
	(0.2340)	(0.2311)
Job Insecurity Partner_Mean	-0.6893***	-0.6790***
	(0.2326)	(0.2295)
Δ Job Insecurity	-0.9577***	-0.9737***
	(0.2084)	(0.2040)
Δ Job Insecurity Partner	-0.4990**	-0.4956***
	(0.1942)	(0.1895)
Δ Job Insec.#Gender	-0.3325	-0.3334
	(0.2959)	(0.2943)
Δ Job Insec. Partner#Gender	0.3121	0.3219
	(0.2278)	(0.2268)
Time	-0.0785**	-0.0816**
	(0.0325)	(0.0325)
Age	0.0719***	0.0725***
	(0.0087)	(0.0087)
Yrs in Education	0.0161	0.0181
	(0.0341)	(0.0343)
Legislators/Senior Officials/Managers	-0.1640	-0.1667
	(0.3318)	(0.3334)
Professionals	-0.8030***	-0.7839**
	(0.3106)	(0.3112)
Techn./Assoc. Profess.	-0.3539	-0.3278
	(0.2721)	(0.2716)
Clerks	-0.6117**	-0.5814**
	(0.2951)	(0.2939)
Service/Sales Workers	0.1965	0.2527
	(0.3011)	(0.2992)
Agric./Fishery/Craft/Trade Workers	0.0801	0.0901
	(0.2870)	(0.2893)
Plant/Machine Operators/Assemblers	0.4552	0.4702
	(0.3278)	(0.3308)

Table 26 (continued): Two-Level Model vs. Three-Level Model - Hybrid Models

Level 3 Variance		25.1730***
		(0.4730)
Level 2 Variance		14.7635***
		(0.4422)
Women	44.6300***	
	(0.7281)	
Men	34.5533***	
	(0.6364)	
Level 1 Variance	55.5640***	56.3264***
	(0.3948)	(0.3725)
F(ΔJI;ΔJI#Gender)	54.18***	59.92***
F(ΔPJI;ΔPJI#Gender)	6.67**	6.92**
AIC	224790.9	224832.3
BIC	225016.4	225016.0
-2 Log likelihood	224736.8	224788.2
Number of Observations	31,316	31,316
Number of Individuals	12,826	12,826
Number of Dyads	6,376	6,376

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Dependent variable: MCS. Estimation procedure: ML. Base category for Gender: Men. Base category for occupation dummy variables: Elementary occupations.

Gender also displays a slightly lower estimation result by 0.0026 points in the two-level Hybrid Model compared to the three-level Hybrid Model. The level of significance of the time variable is constant in both models. Comparing the estimation results for the control variables of the two-level Hybrid Model with those of the three-level Hybrid Model, deviations regarding the effect sizes of the coefficients are identified. The coefficient signs however display the same results in both Hybrid Models. The estimated levels of significance are predominantly the same. Only the level of significance of the occupation dummy variable, controlling for the occupation group of professionals, displays a different level of significance while comparing both Hybrid Models. Once an additional level is included into the Hybrid Model, the level of significance decreases from the 1%-level to the 5%-level of significance. The largest deviation regarding the effect sizes of the control variables can be found for the occupation dummy variable, which measures if an individual works as a service worker, a shop sales worker or a market sales worker. The deviation amounts to 0.0562 points. The deviations of the estimation results for the other con-

trol variables rank between 0.0006 points regarding the years in education and 0.0303 points considering the occupation group of clerks.

The relative model fit indices show heterogeneous results. The AIC and the -2LL display lower values for the two-level Hybrid Model than for the three-level Hybrid Model and the BIC value displays a lower value for the three-level Hybrid Model than for the two-level Hybrid Model. However, the difference between the BIC values are rather small. Using a likelihood-ratio test to test the null hypothesis $H0$, that the three-level Hybrid Model fits the data even significantly better than the two-level Hybrid Model, $H0$ can be rejected. The results are displayed in Table 27 and indicate that the Hybrid Model with two levels fits the data significantly better than the Hybrid Model with three levels.

Table 27: Likelihood-Ratio Test – Three-Level vs. Two-Level Hybrid Model

Likelihood-Ratio Test	LR chi2(5) = 51.37
(Assumption: 2-Level nested in 3-Level APIM)	Prob>chi2 = 0.0000

8 Discussion

The results of the empirical analysis are in line with the assumed negative spillover and crossover hypotheses of job insecurity to the mental health status. Furthermore, the results support the assumed different vulnerability of job insecurity for women and men. The MLM with two-levels as well as the MLM with three-levels display significant relationships between job insecurity, partner's job insecurity and the mental health status for women and men.

On average, a woman who suffers from job insecurity displays a significantly worse mental health status than a woman who does not suffer from job insecurity. Furthermore, a man who suffers from job insecurity displays a significantly worse mental health status than a man who does not suffer from job insecurity. These results support the first part of the Spillover-Crossover Model for women and for men. Additionally, it confirms the negative spillover hypothesis of job insecurity for both sexes and answers the first research question regarding spillover of job insecurity to the mental health status of an individual, suffering from job insecurity. The results are in line with previous research that examines the relationship between job insecurity and mental health. For example, a similar result is identified for Germany in recent research by Reichert and Tauchmann (2017) and Otterbach and Sousa-Poza (2016). Reichert and Tauchmann (2017) find a significant negative effect of workforce reduction (as a measurement for objective job insecurity) on the mental health status of individuals in Germany. In addition, they display that this effect is significantly mediated by subjective job insecurity, using the GSOEP from 2002 to 2010. Also Otterbach and Sousa-Poza (2016) examine the relationship between job insecurity and the mental health of individuals, living in Germany. They use data of the GSOEP for the years 1997 and 1999 up to 2009 and concentrate on subjective job insecurity. The empirical findings, which are found by Otterbach and Sousa-Poza (2016), display a significant negative relationship between job insecurity and the mental health status of individuals suffering from job insecurity.[104] Furthermore, they identify that the negative effect of job insecurity is even more harmful, when individuals report a low employability (Otterbach and Sousa-Poza, 2016).[105]

[104] A similar study for Germany is represented by Bethge et al. (2008) using data of the GSOEP between 2003 and 2006. They identify a significant negative relationship between job insecurity and general health.

[105] Employability is captured by asking individuals, whether it would be easy, difficult, or impossible to find a new job if they were looking for one or to find a job that is at least as good as their current one if they would lose their job today (Otterbach and Sousa-Poza, 2016).

Further results examining individuals outside of Germany can verify a significant relationship between job insecurity and mental health, as well. One of the recent studies for example comes from Fiori et al. (2016) for individuals, living in Italy. Fiori et al. (2016) examine the relationship between job insecurity and the mental health status between 2005 and 2012, using a representative health survey for Italy by the Italian National Institute of Statistics (ISTAT). Concentrating on individuals aged between 18 and 38, they find a significant relation between job insecurity and the mental health status. Furthermore, they identify that the relationship is partly explained by financial difficulties. Cottini and Ghinetti (2017) examine job insecurity in terms of the fear of job loss, the fear of losing the current job status and the fear of not finding another job, for individuals living in Denmark. They use data of Denmark, which is collected from different sources for the years 1995, 2002 and 2005. Their empirical results determine that job insecurity negatively affects mental health. In addition, they identify that mental health differs among occupation to the disadvantage of white collar workers. A further recent study in this field of research comes from Lam et al. (2014). Lam et al. (2014) identify a significant relationship between job insecurity and mental health for the USA. They examine data of job insecurity in 2006 and 2010 and hence before and after the global economic downturn in 2008 and 2009. For their examination, they use data of the cross-sectional General Social Survey of adults living in the USA. While measuring job insecurity in terms of the probability of losing a job, they find that higher levels of job insecurity are associated with lower levels of happiness and more days of poor mental health (Lam et al., 2014). Furthermore, they find evidence for period effects. The effect of job insecurity on mental health is found to be stronger in times of uncertain economy (Lam et al., 2014).

Regarding the present analysis, period effects respectively time trends are captured due to the inclusion of the time variable in each of the estimated models. The time variable is included in the Base APIMs, the Full APIMs, the Lag Models as well as the Hybrid Models in order to prevent biases due to existing time trends in the used data. The significant results of the time variables in the Over-time Standard APIMs indicate that such time trends are actually present in the underlying data, used for the present analysis. The robustness of such time trends is furthermore supported by significant effects, when it is controlled for temporal asymmetry, unobserved heterogeneity and omitted variables. Therefore, the results of the present analysis are also in line with the study by Lam et al. (2014) regarding period effects, respectively time trends.

Further empirical evidence, supporting spillover of job security to the mental health status can be found in previous literature, for example by Hellgren and Sverke (2003) or Näswall et al. (2005a) for Sweden, by Størseth (2006) for Norway, by Kopp et al. (2007) for Hungary, by Chirumbolo and Areni (2010) for Italy or by Tomas and Seršić (2015) for Croatia.

The presented empirical evidence of previous studies displays that negative spillover from job insecurity to the mental health status exists within different countries and national cultures. This result is especially interesting with regard to the empirical examinations of divergence between uncertainty avoidance across countries by Hofstede (1984, 2003); Hofstede et al. (2010); Hofstede and Hofstede (2012). Uncertainty avoidance represents one of meanwhile six dimensions of national cultures and deals with the tolerance of uncertainty and ambiguity within a given society. The dimensions of national cultures were identified in empirical examinations of up to 93 different countries for some dimensions by examining cultural effects on the values and behavior of the members of a given society (Hofstede et al., 2010; Hofstede and Hofstede, 2012).[106] The dimension of Uncertainty Avoidance is presented by an Uncertainty Avoidance Index between 1 and 120, whereas higher values present higher uncertainty avoidance (Hofstede, 1984, 2003; Hofstede et al., 2010; Hofstede and Hofstede, 2012). Considering this, it can be assumed that in a country with a high Uncertainty Avoidance Index job insecurity is more negatively related to mental health, than in a country with a low Uncertainty Avoidance Index. For Germany, a value of the Uncertainty Avoidance Index of 65 is identified. Even higher values are identified for Italy (75), Croatia (80), Hungary (82), lower values however are identified for Norway (50), the USA (46), Sweden (29) or Denmark (23) (Hofstede, 1984, 2003; Hofstede et al., 2010; Hofstede and Hofstede, 2012). However, the effect sizes of previous studies can not be compared to those of the current analysis, due to the different samples in each of the studies. Nevertheless a spillover of job insecurity to the mental health status is in general identified in each of these countries respectively cultures presented above. The divergence of uncertainty avoidance across different national cultures is therefore not reflected regarding job insecurity and hence uncertainty regarding job security.

Summarized, the result of the present analysis makes a contribution to the existence of a spillover from job insecurity to the mental health status for Germany, using representative data up to 2012. The significant results for women and men even remain, when the control variables age, education and occupa-

[106] The other five dimensions are: Power Distance, Individualism, Masculinity, Long-Term Orientation and Indulgence (Hofstede et al., 2010; Hofstede and Hofstede, 2012).

tion are included into the model. In addition, spillover of job insecurity to the mental health status is still identified for women and men, when temporal asymmetry, unobserved heterogeneity and omitted variables are taken into consideration. Hence, the robustness checks indicate that the results are stable although varying regarding the effect sizes.

The negative spillover of job insecurity to the mental health status in the present analysis is found to differ by gender. A stronger relationship between job insecurity and the mental health status can thereby be identified for male individuals. The significant gender difference even remains, when it is controlled for age, education and the occupation dummy variables based on the ISCO. Furthermore, the different vulnerability of women and men is even found, when temporal asymmetry, unobserved heterogeneity and omitted variables are taken into consideration. The different spillover effects among gender are in line with the Social Role Theory and with previous research, for example by Lam et al. (2014). Lam et al. (2014) find gender differences in the relationship between job insecurity and mental health to the disadvantage of men. Another study by Cheng et al. (2005) finds evidence for gender differences in which again men display a stronger negative relation between job insecurity and mental health in Taiwan.[107] However, there are also some studies identifying contrary results. For example, Kalil et al. (2010) find evidence for a stronger relationship between job insecurity and the mental health status for women using data of Illinois, USA.[108] Summarizing, an inconsistent picture in previous literature on job insecurity and mental health, regarding gender differences in the relationship between job insecurity and the mental health status, appears (Kim and von dem Knesebeck, 2015).

A study by Gaunt and Benjamin from 2007 gives a possible explanation of these different findings in previous research, considering gender differences. Gaunt and Benjamin (2007) show that the relationship between gender, job insecurity and stress is moderated by gender ideology. More detailed, they find out that the relationship between job insecurity and stress is stronger for traditional men than for traditional women. Furthermore, they identify that for egalitarian men and egalitarian women, the effect of job insecurity on stress is however similar (Gaunt and Benjamin, 2007). Looking at these results by Gaunt and Benjamin (2007) with regards to the Social Role Theory, the results for traditional men and women are easily traceable. The traditional gender ideology suggests that men take the role of breadwinner and women take over the responsibility for household and childcare (Gaunt and Benjamin,

[107] For further studies see e.g. De Witte (1999), Pelfrene et al. (2003) or Kopp et al. (2007).
[108] For further studies see e.g. a meta analysis by Cheng and Chan (2008).

2007). This differentiation is in line with the assumption of the Social Role Theory that women have a stronger identification with the family role and that men have a stronger identification with the work role (Eagly et al., 2000). These different identifications in turn lead to a different vulnerability regarding experiences in the different roles (Simon, 1992).

The result, that the vulnerability of job insecurity for egalitarian women and egalitarian men is similar, indicates that gender roles and gender stereotypes seem to be in change. The egalitarian gender ideology suggests a more equal distribution of the participation of women and men in the breadwinner, the household and childcare roles (Gaunt and Benjamin, 2007). This modification of gender roles is however also considered in the Social Role Theory. The Social Role Theory assumes that such modification is due to changes in the social role structure (Eagly et al., 2000). Eagly et al. (2000) expect that gender roles are in flux but have not clearly changed yet. This view is fully supported by the different results, which are found in previous research regarding gender. Furthermore, it is in line with the findings by Gaunt and Benjamin (2007).

Regarding the results of the present analysis, it can be assumed that for women and men, who are living together in one household in Germany between 2002 and 2012, the traditional gender ideology is still prevalent. This is assumed because of the significant differences of the spillover effects of job insecurity to the mental health status for women and men. Following the Social Role Theory and previous literature on different vulnerability of role strain (Kessler and McLeod, 1984; Wheaton, 1990; Simon, 1992; Thoits, 1992), the stronger relationship between job insecurity and the mental health status of men can be traced back to a strong identification of men with the work role, leading to a stronger vulnerability of stress experienced in the work-role (Simon, 1992). The less harmful effect of job insecurity to the mental health status for women can however be assumed to be traced back to a stronger identification with the family-role, leading to a less vulnerability to stress in the work-role. This interpretation of the significant gender differences, identified in the present analysis, are in line with previous research about gender roles in Germany for example by Bredtmann (2014), Ancharski (2015), Camp et al. (2016) or Wimmer (2016), who still identify the prevalence of labor market division and role attribution in Germany until today, while examining the participation of women and men in the German labor market.

The additional results of the present analysis, which could be identified, however go beyond previous empirical evidence of the relationship between job insecurity and the mental health status of individuals. The results do not only

display a significant spillover of job insecurity to the mental health status, but also a significant crossover of job insecurity to the mental health status. Individuals, living in a household with a partner suffering from job insecurity on average display a worse mental health status, than individuals with a partner not suffering from job insecurity. These partner effects are found to be significant for women and men in the two-level as well as in the three-level Over-time Standard APIM. Also, while including the control variables age, education and the occupation dummy variables, the results mainly stay the same, indicating the robustness of the findings. Therefore, the results confirm the second part of the Spillover-Crossover Model, the inter-individual transmission of experiences across individuals. Furthermore, the results are in line with previous literature, examining the relationship between the employment status of an individual and the health status of the individual and the individual's partner. For example, Marcus (2013) could be mentioned. He examines the relationship between unemployment and the mental health status of spouses, using data of the GSOEP between 2002 and 2010. Marcus (2013) finds empirical evidence for such a crossover of unemployment to the spouse's mental health status. He identifies crossover from women's experience of unemployment to men's mental health status as well as from men's unemployment experience to women's mental health status. Similar results could be identified by Mendolia (2014) for individuals living in Britain. Furthermore, the result is in line with Bünnings et al. (2017), identifying a relationship between the fear of unemployment and spouse's mental health status however even not examining a crossover according to the Spillover-Crossover Model.

The results of the present analysis make a contribution to previous research on the crossover of the employment status to a partner, while considering job insecurity as an employment status of „unsafe". Furthermore, the results are in line with previous literature examining crossover of several job demands. For example the study by Shimazu et al. (2011) or by Bakker et al. (2012), which were presented in Chapter 3.1, should be mentioned here. Their results display empirical evidence for a crossover of workaholism, respectively a loss of engagement.[109] Therefore, the present empirical evidence for a crossover of job insecurity to an individuals' partner additionally makes a contribution to research on crossover of job demands.

However, it has to be taken into account, that women's significant partner effect and hence the effect from women's job insecurity on men's mental health status disappears, when considering temporal asymmetry in the three-level

[109] Additional evidence could be found by Sanz-Vergel et al. (2012), Bakker et al. (2013) or Totenhagen et al. (2017).

Lag Model. Additionally, women's partner effect loses in power of significance in the two-level Lag Model compared to the two-level Full APIM. This implies that women's job insecurity at $t-1$ and hence in the previous year, is not significant, respectively only significant at the 10%-level, related to the mental health status of men at time t. Nevertheless, this result does not query the empirical evidence for women's partner effect on men's mental health status, when both variables are elaborated at time t. The temporal asymmetry between women's job insecurity and men's mental health status, which is used to make a contribution to a causal interpretation of the detected relationships, can not be confirmed using three-level modeling. Due to the fact that the significant relationship still remains while it is controlled for unobserved heterogeneity in the Full APIMs, the crossover of job insecurity is still considered to be verified by the results. The three-level and the two-level Hybrid Models support the crossover of job insecurity to the mental health status. Women's job insecurity as well as men's job insecurity are identified to crossover to the partner's mental health status. Both models display significant effects of all relevant variables. Although the effect sizes of the coefficients decrease once it is controlled for unobserved heterogeneity and omitted variables, the significant relationships are still present.[110]

Similar gender differences as for spillover of job insecurity are also found regarding crossover of job insecurity. As it is assumed, men's partner effect and hence the effect of men's job insecurity on women's mental health status displays a more negative effect size than women's partner effect. This result is in line with the Social Role Theory. The result supports the assumption that the family and the work role are differently adopted by women and men in Germany which leads to a different vulnerability in role strain. Due to the stronger identification of men with the work role, job insecurity as work-role strain is more harmful regarding mental health (Simon, 1992; Eagly et al., 2000). Looking at a direct crossover from men to women due to the mental health status of men based on the Theory of Emotional Contagion by Hatfield et al. (1993), the more affected mental health status of men is also more harmful for women's mental health status. Considering indirect crossover based on considerations of the Social Identity Theory by Tajfel and Turner (1979), the stronger vulnerability of job insecurity for men leads to a more unbalanced social interaction at the home-domain and hence also affects women's mental health status more harmfully than women's job insecurity would do.

[110] Of course, as mentioned before, the interpretation of the effect of the Hybrid Models has to be conducted with regard to the estimated within-individual part of job insecurity instead of job insecurity in general.

Therefore, the different vulnerability of job insecurity for women and men, which is identified in the present analysis in terms of crossover, supports the assumption that the traditional gender ideology is still prevalent. Traditional role attribution is assumed for women and men living together in one household in Germany between 2002 and 2012. This is again in line with previous literature on division of labor and gender roles in Germany by Bredtmann (2014), Ancharski (2015), Camp et al. (2016) or Wimmer (2016). Furthermore, considering crossover of job insecurity, it could be identified, that men's partner effect is displayed to be highly significant at a 1%-level of significance when job insecurity is measured in $t-1$ in the estimated Lag Models. Hence, contrary to women's partner effect, men's experienced job insecurity in $t-1$ significantly affecs women's mental health status in t. This implies that men's job insecurity is not only more harmful for women's mental health status, but also seems to be more long-lasting than women's partner effect within couples in Germany.

Regarding the used control variables, a significant relation between age and the mental health status is identified in the multilevel analysis. This result is in line with the descriptive statistics of the present analysis and with previous literature that identifies age as a relevant control variable (e.g. Jacobson and Hartley (1991), Mohr (2000) or Minnotte and Yucel (2017)). Contrary to the assumption, education is not found to be significantly related to the mental health status in the two-level as well as in the three-level Over-time Standard APIM. Although the correlation matrix displays a significant negative correlation, a significant relationship between education and the mental health status can not be confirmed using MLM, except when job insecurity is included as a lag variable in the Over-time Standard APIMs. This result is thereby not in accordance with previous literature that identifies education as an important control variable regarding job insecurity and the mental health status (e.g. Jacobson and Hartley (1991), Fiori et al. (2016) or Minnotte and Yucel (2017)). As one might assume, the insignificance of education is not associated with the joint inclusion of education and occupation. As an additional robustness check, education is included into all estimated models without including occupation additionally. The coefficient of the variable measuring years in education still remains insignificant in the Over-time Standard APIMs and the Hybrid Models.

The results of the occupation dummy variables display that professionals and clerks show on average a worse mental health than individuals in elementary occupations. Hence, the occupation group an individual belongs to matters

regarding the relationship between job insecurity and the metal health status. This result is in line with previous literature, for example by Schütte et al. (2015), Fiori et al. (2016), Cottini and Ghinetti (2017) or Reichert and Tauchmann (2017). While controlling for unobserved heterogeneity and omitted variable bias, the significant effects of the occupation groups of professionals and clerks are still existent. However, a significant relationship between the occupation dummy variables and the mental health status is not identified while checking for temporary asymmetry.

Combining the results for the variable measuring education as well as the variables controlling for the different occupation groups, it appears that the effects are alternately estimated to be significant, comparing the Full APIMs and the Hybrid Models with the Lag Models. In the Full APIM as well as in the Hybrid models, occupation displays significant results while education does not. In the Lag Models however, education displays a significant result while occupation does not. The significant results of some of the occupation groups are robust in terms of unobserved heterogeneity. This implies that there actually exists an influence of occupation regarding mental health, because the effects are not biased due to unobserved characteristics or omitted variables. The effect may not be significant in the Lag Models due to the reduced number of observations while estimating the Lag Models. Because not all individuals are observed over all included years, the number of observations used in the Lag Models is reduced by about 20% compared to the Full APIMs and the Hybrid Models. This reduced number of observations leads to a less representative pool of observations of each occupation group which can in turn may lead to biased results of the occupation dummy variables in the Lag Models. Due to the high correlation between occupation and education of 0.541, it is possible that the real effect of occupation, which may not be estimated due to the reduced number of occupation, is expressed in education, leading education to be significant. Comprehensively, it can be stated that there is a significant influence related with occupation and education on the mental health status. Furthermore, occupation and education are obviously connected, because the different occupation groups require different levels of education. Therefore, it could be assumed that there are unobserved characteristics which apply to the individuals in different occupations and with different levels of education. Hence, such unobserved characteristics are coherent with occupation as well as with education. The Hybrid Models enable to control for such unobserved characteristics so that the significant effect of occupation in the Hybrid Model is assumed to be due to actual differences between different occupation groups. However, the significant effect of education in the Lag Models, in which it is

not controlled for unobserved heterogeneity, is assumed to arise because of unobserved characteristics and not due to different levels of the mental health status among different levels of education. This assumption is in line with the descriptive statistics of the mental health status across different education groups displayed in Table 4 in Chapter 7.1, where it is demonstrated that different educational backgrounds do not play a very important decisive role for the mental health status, because each education group average score is near the sample average score of the mental health status.

Summarized, regarding the content-related research gap, the existence of a spillover of job insecurity to the mental health status is confirmed. Hence, the first research question can be answered by the results. Furthermore, the results support the first part of the Spillover-Crossover Model and make a contribution to the existing research on the relationship between job insecurity and an individual's mental health status by displaying a significant relationship for a present and representative longitudinal dataset of Germany. The existence of crossover of job insecurity to the mental health status of an individual is verified as well. Hence, the second research question is additionally answered by the results. Furthermore, the results support the second part of the Spillover-Crossover Model and make a contribution to the research about crossover of an employment status as well as to the research about the crossover of job demands. Altogether, the Spillover-Crossover Model for job insecurity and the mental health status is empirically confirmed for individuals living together in one household in Germany between 2002 and 2012. Additionally, spillover and crossover are found to be different for women and men, as assumed on the basis of the Social Role Theory. Gender role beliefs and gender stereotypes still seem to affect the process of socialization of girls and boys in Germany up to 2012, which leads women to have a stronger identification with the family role and men to have a stronger identification with the work role. The third and fourth research question are answered by this results and the aim of making a contribution to the theory development of spillover and crossover can be reached. Comprehensively, the identified content-related research gap is closed by the empirical findings.

In order to answer the research question, which arises by the methodological research gap, Figure 17 displays the estimation results of the actor and the partner effects for women and men in the different estimation models. In the upper part of Figure 17, the results of the actor and partner effects for women and men of the two-level and the three-level Full APIMs are displayed. In the middle part of 17, the results of the actor and partner effects of the two-level

and the three-level Lag Models are presented. Finally, the lower part of Figure 17 shows the results of the actor and partner effects for women and men of the the two-level and the three-level Hybrid Models.

Looking at the upper part of Figure 17, it can be seen, as already determined, that the results of the two-level as well as of the three-level Over-time Standard APIM are identical regarding significance and coefficient signs. Furthermore, it appears that the actor effect of women only slightly differs between the estimation results of the two-level Full APIM and the three-level Full APIM and that the difference of the partner effect from men to women is rather small. This leads to the conclusion, that the directly estimated effects on women's mental health status only differ slightly when comparing two-level and three-level modeling. In contrast, looking at the results of the estimated interaction terms, great differences between those of the two-level Full APIM and those of the three-level Full APIM can be found. Especially, the actor effect of men varies widely. Taking into consideration that the model comparison, using the AIC, the BIC and the -2LL value, identifies the two-level model to fit the longitudinal dyadic data significantly better than the three-level model, the two-level model seems to estimate the interaction effects more accurate than the three-level model does. This result is in line with Hoffman (2015), who points out that in a three-level model for dyadic data, the between-group effect and the within-group effect are not likely to be well distinguished, because the group only consists of two members, which especially appears when actor and partner effects are considered (Hoffman, 2015).

The comparison of the two-level and the three-level Lag Models in the middle part of Figure 17 shows similar results. Also here, the interaction effects display the largest deviation in effect size. Generally, this is not surprising as the only difference from the model above is the lagged independent variable job insecurity, respectively partner's job insecurity. The results of the Lag Models however display a further difference. The interaction effect does not just differ in effect size but also in significance. A model comparison thereby displays different results considering the AIC and the BIC values. The AIC and the BIC differ in the way they punish the complexity of the model, whereas the BIC prefers less complex models (Kuha, 2004). In the present case, the three-level Lag Model is the less complex one. Despite of the additional level in the three-level Lag Model, the additional dummy variables female and male, in the two-level Lag Model lead the two-level Lag Model to be more complex. Hence, it is not remarkable, that the BIC displays a lower value for the three-level Lag Model than for the more complex two-level Lag Model. The heterogeneous

results of the AIC and the BIC values indicate that the model fit of the two-level Lag Model and the three-level Lag Model are very similar. A likelihood-ratio test however supports the two-level Lag Model.

Regarding the two-level and the three-level Hybrid Models in the lower part of Figure 17, the model comparison also shows an inconsistent result. While controlling for unobserved heterogeneity, the two-level Hybrid Model fits the data significantly better than the three-level Hybrid Model following the AIC value and the -2LL value. The BIC however displays a lower value for the three-level Hybrid Model. Because the difference is very slight and against the background that the BIC prefers less complex models, the inconsistent result of the relative model fit indices are neglected and the result of the likelihood-ratio test is considered. The likelihood-ratio test for the two-level and the three-level Hybrid Model indicate that the Hybrid Model with two levels fits the data significantly better than the Hybrid Model with three levels. Looking at the estimation results of the Hybrid Models in detail, it can be seen that the differences between the two-level and the three-level modeling are slightly. The Hybrid Models display the lowest differences between two-level modeling and three-level modeling compared to the Over-time Standard APIMs and the Lag Models.

Comprehensively, it could be shown that a two-level Over-time Standard APIM fits the longitudinal dyadic data significantly better than a three-level Over-time Standard APIM. Thereby, the two-level Over-time Standard APIM seems to estimate especially the interaction effects more accurate than the three-level Over-time Standard APIM. This is also true, when it is controlled for temporal asymmetry in the Lag Models. However, controlling for unobserved heterogeneity and omitted variables seems to solve a part of the assumed biases in the three-level Over-time Standard APIM and the three-level Lag Model. The differences between the two-level and the three-level modeling of actor and partner effects decrease. The results support the recommendations of Bolger and Laurenceau (2013) and Kashy and Donnellan (2012), since modeling two-levels and hence occasions as crossed within individuals displays a better model fit than modeling them as nested within individuals in each of the models. Nevertheless, the differences between the two-level and the three-level modeling in general are rather small and do not differ in the signs of the coefficients and within the levels of significance, with one exception. The differences are exclusively presented considering the effect sizes of the coefficients to a rather small extent. Especially, the estimation results of the Hybrid Models hardly show any differences between two-level modeling and three-level modeling.

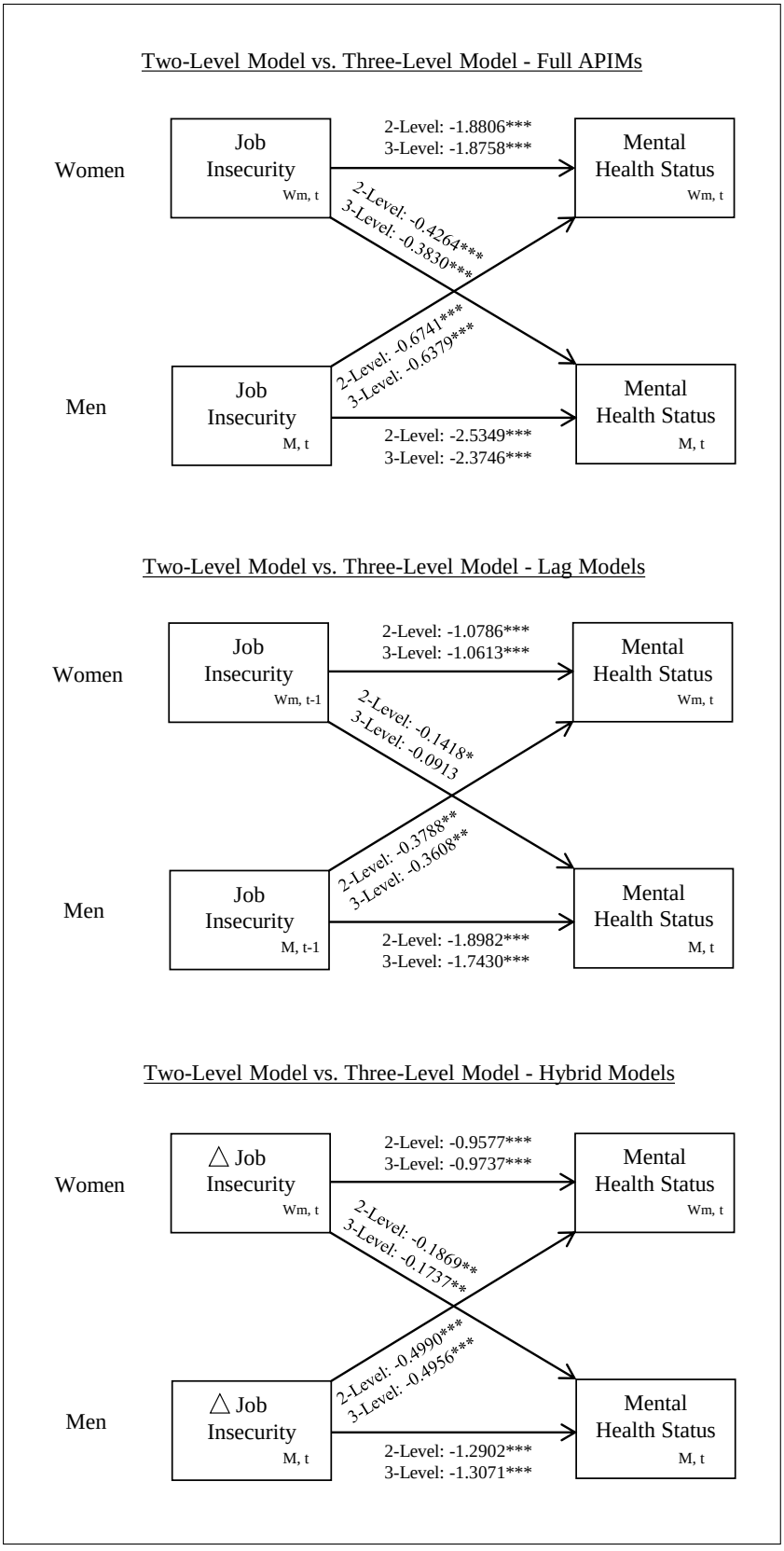

Figure 17: Comparison of the Actor and Partner Effects of the Different Estimation Models.
(Source: Own presentation.)

9 Limitations

The results of the present analysis are checked for robustness in the light of various robustness checks regarding control variables, temporary asymmetry, unobserved heterogeneity and omitted variables. However, some limitations restrict the findings of the present analysis. First to be mentioned is the limitation regarding the estimation results in the different estimation models, which arises due to the used measurement of job insecurity. Furthermore, to be mentioned is the limitation due to the problem of unobserved heterogeneity and omitted variables, which may bias the results of the Over-time Standard APIMs and the Lag Models. In addition, limitations have to be considered, arising due to the used data and the made sample restrictions. Finally, limitations, related to the result of the comparison of two-level and three-level modeling, occur due to the underlying data.

The first and one of the most relevant limitation refers to the interpretation of the estimated coefficients. A possible bias is assumed to arise due to the measurement method of job insecurity. Although a single-item measurement of job insecurity is widespread and recommended in several studies (e.g. De Witte (1999), Mohr (2000), Burgard et al. (2012), Lam et al. (2015), Probst and Jiang (2017)), Sverke et al. (2002) present that a single-item measure of job insecurity tends to underestimate the relationship between job insecurity and an outcome variable. Hence, while interpreting the effect size of the variables, which measure job insecurity as well as partner's job insecurity, it should be considered that due to the single-item measurement of job insecurity in the GSOEP, the relationship between job insecurity and the mental health status may be underestimated. Nevertheless, while comparing the estimation results of the Over-time Standard APIMs with those of the Lag Models and those of the Hybrid Models, this circumstance is assumed to be negligible. Due to the fact, that single-item measurement of job insecurity is given in all the estimated models, the results of all models will be biased in terms of underestimated effect sizes. Hence, the problem should be of no consequence in model comparison, but in the direct interpretation of the effect sizes of each estimation model. In addition, while using this specific single-item measurement of job insecurity in the GSOEP, job insecurity is elaborated indirectly through job security. This kind of measurement is only applicable based on the assumption, that no job security equals job insecurity and that no job insecurity equals job security, which is given as long as job insecurity and job security are assumed to represent the extreme forms of one continuum (Johnson et al., 1984; Sverke et al., 2002; Virtanen et al., 2002). This assumption should therefore be taken

into consideration, while interpreting the estimation results.

While estimating the Hybrid Models, a significant difference between the within-individual part and the between-individual part of the variable job insecurity as well as of the variable partner's job insecurity is identified. This indicates that unobserved heterogeneity seems to exist in the underlying data. The presence of unobserved heterogeneity in the data may additionally result in biased effect sizes of the coefficients in the Over-time Standard APIMs as well as in the Lag Models, where it is not controlled for unobserved heterogeneity. Due to this limitation, the discussion of the content-related results in Chapter 8 is restricted to the interpretation of significance and the signs of the estimated coefficients. Of course, unobserved heterogeneity may also lead to biases regarding significance and coefficient signs (Wooldridge, 2010; Morgan, 2013). However, biased estimations of significance and coefficient signs of the independent variables in the Over-time Full APIMs are not assumed in the present analysis, because the estimated significance and coefficient signs of the independent variables are supported by the Hybrid Models, where it is controlled for unobserved heterogeneity. Regarding the Hybrid Models, it has to be taken into consideration that they do not estimate the general effect of job insecurity like the Over-time Standard APIMs or the Lag Models, but the within-individual parts and between-individual parts of the variables job insecurity and partner's job insecurity. Nevertheless, the within-individual part estimated in the Hybrid Models is comparable with job insecurity and partner's job insecurity in the Over-time Standard APIMs and the Lag Models and can be used to verify the assumed hypothesis. In summary, the interpretation of the effect sizes of the Over-time Standard APIMs as well as of the Lag Models should occur in consideration of the single-item measurement of job insecurity and potential unobserved heterogeneity. The interpretation of the Hybrid Models however should occur in consideration of the single-item measurement of job insecurity.

The next important limitation is represented by the limited interpretation of the results regarding causality. Although previous literature has identified a causal direction from job insecurity to the mental health status and not the other way around (Hellgren and Sverke, 2003),[111] a causal interpretation of the present results should be done carefully. Indeed, it is tried to reach a causal interpretation by following the recommendations by Kube (1991), Hildebrandt

[111] Hellgren and Sverke (2003) use longitudinal data of a Swedish retail company between 1995 and 1996 to identify the direction of the relationship between job insecurity and mental health as well as physical health. Their results display a significant cross-lagged effect of job insecurity to the mental health status, the effect of mental and physical health on job insecurity however is found to be insignificant (Hellgren and Sverke, 2003).

et al. (1992), Haenecke (2002), Herrmann et al. (2008), Trommsdorff and Teichert (2011), Döring and Bortz (2016). The hypotheses of the relationships between job insecurity, partner's job insecurity and the mental health status are derived theoretically for women and for men. Additionally, an empirical correlation between the hypothesized variables is present by empirical examination. Furthermore, a temporal asymmetry between job insecurity, partner's job insecurity and the mental health status is detected. Finally, effects due to additional variables are tried to be excluded by estimating Hybrid Models, where it is controlled for unobserved heterogeneity and omitted variables. Unfortunately, because of the used data, it is not possible to include further variables, which are identified as important in previous research, next to age, education and occupation in the Over-time Standard APIMs and the Lag Models. Here, for example a variable, which measures the gender role ideology of the observed individuals has to be mentioned. Previous results suggest that the relationship between job insecurity, partner's job insecurity, the mental health status and gender may be influenced by the gender ideology of individuals (Gaunt and Benjamin, 2007). An empirical examination is however not possible in the present analysis, because a measurement of gender ideology is not included in the used data.[112] Therefore, the interpretation of the identified different vulnerability of job insecurity for women and men, due to a common traditional gender ideology among individuals in Germany between 2002 and 2012, can not be supported by empirical examination and remains an assumption.

Next to the missing availability of some important control variables, further variables are excluded because of a restriction regarding the extent of used control variables for the present analysis. Only control variables are selected, which are found to have a significant influence in more than three studies which are identified in a literature research between 1988 and 2017 (Chapter 5.2). Therefore, some variables are not included, although available in the GSOEP. For example variables controlling for the marital status and the existence of children can be mentioned. On the one hand, considering the Social Role Theory, it could be assumed that for married men the consequences of job insecurity on the mental health status are more harmful than for not married men, because the work role in terms of earning money for a family could be assumed to be more important for married men than for not married men (Eagly and Steffen, 1984; Eagly and Wood, 1991; De Witte, 1999; Eagly et al., 2000). The same could be assumed for men with children and hence fathers

[112] Another control variable which can not be used is for example social support (Kinnunen and Nätti, 1994; Mohr, 2000; Marchand and Blanc, 2011; Minnotte and Yucel, 2017).

who suffer from job insecurity. On the other hand, following the Social Role Theory, it could be assumed that the consequences of job insecurity are less harmful for married women and mothers than for non married women without children (Eagly and Steffen, 1984; Eagly and Wood, 1991; De Witte, 1999; Eagly et al., 2000). A stronger identification with the family-role in terms of taking care of the household and childcare of married women and mothers would lead to a less vulnerability of experiences in the work role (Kessler and McLeod, 1984; Wheaton, 1990; Simon, 1992; Thoits, 1992). However, such assumptions can not be verified by the present analysis as the marital status and the existence of children are not examined. Another example is the variable measuring the employability of an individual who suffers from job insecurity. Employability, defined as the probability of finding a new job when losing the current one, is identified in previous literature to influence the negative effect of job insecurity on mental health (Otterbach and Sousa-Poza, 2016; Cottini and Ghinetti, 2017). This variable is available in the GSOEP, but not included in the present analysis. Nevertheless, as employability is just found to influence the effect size of the already identified effect of job insecurity on the mental health status, not including employability is assumed not to affect the significance of the general results. However, the missing inclusion of important variables restricts the causal interpretation of the results of the Over-time Standard APIMs and the Lag Models, as it may lead to an omitted variable bias. However, the estimation of the Hybrid Models considers the problem of omitted variable bias, by separating the time-varying variables into a within-individual part and a between-individual part (Krause and Urban, 2013). This leads to the fact that the explanatory variables in a Hybrid Model are no longer related to other variables that can not be included in the estimation models (Krause and Urban, 2013). Nevertheless, it still remains that it is impossible to compare the estimation results of job insecurity and partner's job insecurity of the Hybrid Models with those of the Over-time Standard APIMs and those of the Lag Models directly, because the Hybrid Models estimate the effects of the within-individual part and the between-individual part of job insecurity and not the general effect of job insecurity.

Some additional limitations arising due to the selected data of the GSOEP have to be mentioned. By bringing together the empirical results with the theoretical foundation, it has to be taken into consideration that a holistic examination of the overall Spillover-Crossover Model is not possible using the GSOEP. In the Spillover-Crossover Model it is assumed, that spillover of job demands happens due to a work-family conflict and crossover occurs through the well-being status of the partner (direct crossover) or through social inter-

action between partners (indirect crossover) (Bakker and Demerouti, 2013). Because a work-family conflict and social interactions are not questioned in the GSOEP, an empirical examination of the detailed paths of spillover and crossover still remains open. A detailed examination of the existence of the direct and of the indirect crossover can not be conducted and hence a contribution to the Theory of Emotional Contagion and the Social Identity Theory in reference to direct and indirect crossover is limited. Furthermore, the examination of the temporal asymmetry between job insecurity and the mental health status is limited by the missing opportunities regarding time delays, because the GSOEP is an annual survey. The results of the partner effects in the Lag Models and especially the estimation result of women's partner effect in the three-level Lag Model are weak. Based on previous research results, showing that crossover effects especially occur in daily datatsets (e.g. Doumas et al. (2003); Bakker and Xanthopoulou (2009); Davila and Kashy (2009); Song et al. (2011)), it can be assumed that the weak effects of the partner effects in the LAG Models are due to the long time delays of one year in the used data. For example, it might be possible that job insecurity initially causes a poorer mental health status, but that it returns to normal level after some habituation time within one year. Referring to this, it has additionally to be considered, that it is not controlled for the detailed date an individual is questioned in each year. The actual time delay between t and $t-1$ is hence not being used, which should be kept in mind while interpreting the estimation results of the Lag Models. Nevertheless, an own survey, which would enable to question all relevant variables in all relevant time delays, would not enable approximately as much observations as the GSOEP and furthermore a longitudinal questioning over six years. Therefore, the use of a representative longitudinal dyadic dataset based on the GSOEP is still justified.

The restriction to the used sample obviously limits the generalization of the results. The results are true for heterosexual individuals within a couple, living together in one household in Germany between 2002 and 2012. Results for homosexual couples are furthermore especially excluded regarding the examination of gender differences and against the background of the used theoretical foundation. The Spillover-Crossover Model as well as the Social Role Theory do not deal with homosexual individuals. However, there exists previous research on homosexual couples which finds out that the division of unpaid as well as of paid work between individuals in same-sex couples is more equal distributed than it is found to be in heterosexual couples (Goldberg, 2013; Jaspers and Verbakel, 2013; Tornello et al., 2015; Bauer, 2016). This leads to the assumption that differences of spillover and crossover of job insecurity do

not differ in effect size between partners within same-sex couples. A study by Totenhagen et al. (2017) is in line with this assumption. Totenhagen et al. (2017) find evidence for homogenous spillover and crossover of external stress on relationship quality in same-sex couples. Nevertheless, because of limited observations on homosexual couples in the used sample, a separate examination is not pursued further.

Finally, it should be considered that the selection of the MLM with two levels as the more accurate one for longitudinal dyadic data is restricted to the characteristics of the used data. The present analysis consists of a large dataset with 31,316 individual-year observations and 12,826 individuals, which may lead to the rather small differences between the two-level modeling and the three-level modeling. A model comparison can therefore be different in smaller datasets.

10 Conclusion

Three aims should be reached by the present thesis. The first aim is the theoretical processing of the relationship between job insecurity, partner's job insecurity and the mental health status regarding spillover and crossover as well as under the aspect of gender differences. The second aim is set to the verification of the theoretical considerations, while using longitudinal dyadic data representative for Germany. And finally, the third aim is to evaluate two different estimation strategies for those longitudinal dyadic data, MLM with two levels and MLM with three levels. Within these aims, five research question should be addressed. First of all, it is asked, whether a spillover of job insecurity to the mental health status of an individual exists. Secondly, the question is pursued, whether a crossover of job insecurity to the mental health status of the individual's partner, enrolled in a relationship with the individual, exists. Thirdly, it is considered whether a spillover of job insecurity is differently pronounced by women and men. Fourthly, it is asked, whether a crossover of job insecurity to the mental health status is different among gender. And finally, the question is pursued, whether the empirical evidence for the Spillover-Crossover Model differentiated by women and men, should be conducted using three-level modeling or applying two-level modeling, while longitudinal dyadic data is present.

The primal step to reach the first aim is done in Chapter 3.1, after presenting the basic terminology concerning job insecurity and the mental health status by presenting the Spillover-Crossover Model. The theoretical basis is then expanded by the presentation of the Social Role Theory to elaborate gender differences regarding spillover and crossover. In Chapter 4, the basic terminology and the theoretical considerations are united. In this way, the theoretical processing of the relationship between job insecurity and the mental health status can be presented in detail and the first aim of the thesis can be reached. Job insecurity identified as a job demand is, based on the Spillover-Crossover Model, theoretically assumed to cause strain which spills over from the work-domain to the home-domain and leads to a work-family conflict (Bakker and Demerouti, 2013). The work-family conflict is in turn assumed to negatively affect the mental health status of an individual (Bakker and Demerouti, 2013). Furthermore, the spillover of job insecurity to the mental health status is theoretically assumed to be evident in varying degree, depending on gender to the disadvantage of male individuals. This is founded in the Social Role Theory, assuming that gender role beliefs and gender stereotypes affect the process of socialization of girls and boys, which leads women to have a stronger identi-

fication with the family role and men to have a stronger identification with the work role (Eagly and Wood, 2011). Stronger identification with certain roles in turn leads to higher vulnerability of role-stress in the corresponding roles (Kessler and McLeod, 1984; Wheaton, 1990; Simon, 1992; Thoits, 1992). Based on the Spillover-Crossover Model, job insecurity is further theoretically assumed to affect the partner's mental health status by an inter-individual process of crossover. Thereby, direct crossover through the well-being status itself is assumed due to consideration of the Theory of Emotional Contagion by Hatfield et al. (1993) (Bakker and Demerouti, 2013). Indirect crossover through social interaction between partners however can be traced back to considerations of the Social Identity Theory by Tajfel and Turner (1979). Crossover is again assumed to differ among gender. Theoretically founded in the Social Role Theory, the crossover of men's job insecurity to women's job insecurity is assumed to be more harmful than the crossover of women's job insecurity to men's mental health status.

To reach the second aim of the present thesis and hence to verify the theoretically derived hypotheses, an empirical examination using MLM of longitudinal dyadic data of Germany is conducted. Because such data consists of particular characteristics and requires a specific estimation strategy, the data and the used methodology were presented in detail in Chapter 5 and Chapter 6. Dyadic data, as well as longitudinal data are characterized by dependency within the data. Dyadic data is thereby characterized by dependency due to interpersonal interaction and interpersonal relations (Kenny et al., 2006). Longitudinal data however is characterized by dependency due to repeated observations (Hoffman, 2015). Using longitudinal dyadic data, both kinds of dependency have to be taken into consideration and specific estimation models have to be elaborated. Therefore, the theoretically derived hypotheses are verified using an Over-time Standard APIM for job insecurity and the mental health status. Such an estimation model enables to estimate actor effects and hence the effects of an individual's own independent variable on the individuals's own dependent variable, as well as partner effects and hence the effects of an individual's own independent variable on the partner's dependent variable simultaneously (Kenny et al., 2006; Kenny and Ledermann, 2010). Regarding an inconsistency in literature in terms of the estimation strategy of longitudinal dyadic data using an Over-time Standard APIM (Kashy and Donnellan, 2012; Bolger and Laurenceau, 2013; Hoffman, 2015), the Over-time Standard APIM for job insecurity and the mental health status is estimated using MLM with two levels as well as MLM with three levels in comparison.

By examining the theoretically assumed hypotheses, all hypotheses can be empirically confirmed using the different estimation strategies. The research questions, whether a spillover of job insecurity to the mental health status of an individual exists and whether a crossover of job insecurity to the mental health status of the individual's partner, who is in a relationship with the individual, exists, can therefore be validated for women and men. An individual who suffers from job insecurity, on average displays a worse mental health status than an individual who does not suffer from job insecurity. An individual who is in a relationship with a partner who suffers from job insecurity on average displays a worse mental health status than an individual being in a relationship with a partner who does not suffer from job insecurity. Furthermore, the research questions, whether spillover and crossover of job insecurity is different for women and men to the disadvantage of male individuals, can be validated. A man who suffers from job insecurity, on average displays a worse mental health status than a woman, who suffers from job insecurity. A woman, in a relationship with a man who suffers from job insecurity, in addition on average displays a worse mental health status than a man, who is in a relationship with a woman who suffers from job insecurity. These results are additionally proofed by including control variables, controlling for temporal asymmetry between job insecurity and the mental health status and considering unobserved heterogeneity and omitted variables. Hence, also the second aim of the thesis can be achieved. The theoretical considerations are verified and confirmed using longitudinal dyadic data representative for Germany between 2002 and 2012. A contribution is made to the theory development of spillover and crossover, since the Spillover-Crossover Model of job insecurity and the mental health status with regard to the Social Role Theory, is empirically validated. Social Role theory is supported to be prevalent in Germany between 2002 and 2012. Furthermore, the results make a contribution to research on the relationship between job insecurity and the mental health status as well as to research on the crossover of job demands and the employment status.

Finally, the third aim is reached by comparing the empirical results of the two-level Over-time Standard APIM and the three-level Over-time Standard APIM. The two-level Over-time Standard APIM considers occasions to be crossed within individuals and individuals to be nested within dyads, while the three-level Over-time Standard APIM assumes occasions to be nested within individuals and individuals to be nested within dyads. The comparison displays that the results of both models are similar, but while using the AIC, the BIC, the -2LL value and a likelihood-ratio test for model comparison, the

two-level modeling could be identified to fit the underlying longitudinal dyadic data significantly better than the three-level modeling. This is even true, when in both models unobserved heterogeneity and omitted variable bias are taken into consideration. It can be determined, that two-level modeling is especially more suitable regarding the estimation of interaction effects. Nevertheless, the differences between the two-level and the three-level modeling in general are rather small. The research question, whether longitudinal dyadic data should be conducted using three-level modeling or using two-level modeling can hence be validated and a contribution to the methodical approach for longitudinal dyadic data can be made.

Altogether, the present thesis closes the content related as well as the methodological research gaps, which are identified at the beginning of this thesis. The asked research questions are answered by the empirical examination and the results of the present thesis can make different contributions to the existing research in different fields. Furthermore, the present analysis does not only demonstrate the prevalence of job insecurity in Germany, but also illuminates an important consequence arising by job insecurity. Impaired mental illness accounts for 38% of all kinds of illnesses in rich countries and as it hinders individuals to work productively, it costs billions in welfare payments and lost taxes (Layard, 2016).

Nevertheless, further research should be carried out, which arises by the limitations of the present thesis. Especially, the detailed mechanism of spillover and crossover of job insecurity to the mental health status should be considered. Following the Spillover-Crossover Model, spillover of job insecurity happens due to a work-family conflict (Bakker and Demerouti, 2013). Therefore, future research should examine the role of a work-family conflict regarding the relationship between job insecurity and the mental health status. Furthermore, in the Spillover-Crossover Model it is assumed that crossover may occur through the well-being status of the partner and through social interaction between partners (Bakker and Demerouti, 2013). This should be investigated in future research in detail to complete the picture of the Spillover-Crossover Model for job insecurity and the mental health status and make a contribution to the Theory of Emotional Contagion and the Social Identity Theory with regard to direct and indirect crossover. In order to draw a holistic picture about the relationship between job insecurity and the mental health status of an individual who suffers from job insecurity, further variables that are assumed to affect this relationship should be taken into consideration in future research as well. Especially to be mentioned here are gender ideology and

employability as well as the marital status and the existence of children. In addition, further control variables should be considered to prevent the problem of omitted variable bias, while examining spillover and crossover of job insecurity to the mental health status. This is also of interest for future research in terms of making a contribution to the causal interpretation of the relationship between job insecurity, partner's job insecurity and the mental health status. Because of the exclusion of same-sex individuals in the present analysis, future research can make a contribution to the theory development of spillover and crossover by examining particularly same-sex couples. Until now there is hardly any research on spillover and crossover within same sex couples, especially considering spillover and crossover of job demands and job resources.

Appendix

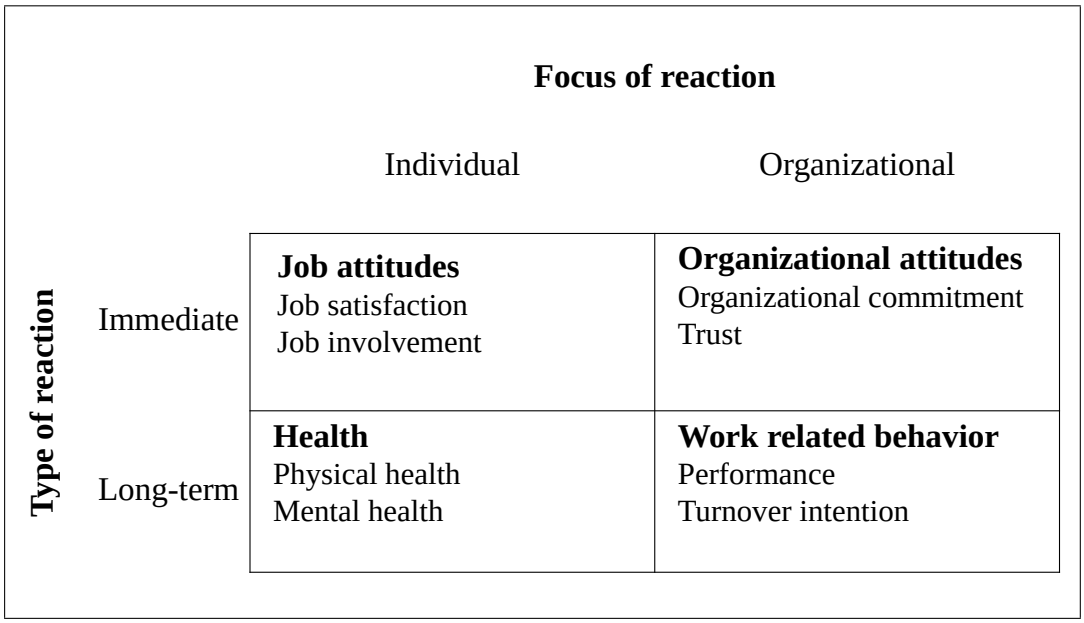

Figure 18: Types of Consequences of Job Insecurity.
(Source: Sverke et al. (2002).)

Table 28: Comparison of the original SF-12v2 MCS and the GSOEP Version of the SF-12v2 MCS

Dimension	Original SF-12v2 MCS	GSOEP SF-12v2 MCS
Vitality	These questions are about how you feel and how things have been with you during the past 4 weeks. For each question, please give the one answer that comes closest to the way you have been feeling. How much of the time during the past 4 weeks...	During the last four weeks, how often did you:
	– Did you have a lot of energy?	– feel energetic?
Mental well-being	These questions are about how you feel and how things have been with you during the past 4 weeks. For each question, please give the one answer that comes closest to the way you have been feeling. How much of the time during the past 4 weeks...	During the last four weeks, how often did you:
	– Have you felt downhearted and depressed?	– feel down and gloomy?
	– Have you felt calm and peaceful?	– feel calm and relaxed?
Social functioning	During the past 4 weeks, how much of the time has your physical health or emotional problems interfered with your social activities (like visiting friends, relatives, etc.)?	During the last four weeks, how often did you feel that due to physical or mental health problems you were limited socially, that is, in contact with friends, acquaintances, or relatives?
Role-emotional	During the past 4 weeks, how much of the time have you had any of the following problems with your work or other regular daily activities as a result of any emotional problems (such as feeling depressed or anxious)?	During the last four weeks, how often did you feel that due to mental health or emotional problems
	– Accomplished less than you would like	– you carried out your work or everyday tasks less thoroughly than usual?
	– Did work or other activities less carefully than usual	– you achieved less than you wanted to at work or in everyday activities?

Note: Response options original SF-12v2: all of the time, most of the time, some of the time, a little of the time. Response options SOEP Version of the SF-12v2: always, often, sometimes, almost never, never. Source: Morfeld et al. (2005) and TNS Infratest Sozialforschung (2013).

Table 29: Summary Statistics

Variable	**Mean**	**Std. Dev.**	**Min.**	**Max.**
Mental Health	50	10	1.81	80.91
Job Insecurity	0.5	0.5	0	1
Gender	0.5	0.5	0	1
Age	44.69	9.14	18	65
Yrs in Education	12.89	2.76	7	18
Legislators/Senior Officials/Managers	0.07	0.26	0	1
Professionals	0.21	0.41	0	1
Techn./Assoc. Profess.	0.24	0.43	0	1
Clerks	0.12	0.32	0	1
Service/Sales Workers	0.1	0.3	0	1
Agric./Fishery/Craft/Trade Workers	0.13	0.34	0	1
Plant/Machine Operators/Assemblers	0.06	0.24	0	1
y2002	0.21	0.4	0	1
y2004	0.18	0.38	0	1
y2006	0.16	0.37	0	1
y2008	0.16	0.36	0	1
y2010	0.14	0.35	0	1
N		31,316		

Table 30: Correlation Matrix including Occupation Dummy Variables

	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1. Mental Health Status	1.000													
2. Job Insecurity	-0.163***	1.000												
3. Job Insecurity Partner	-0.099***	0.313***	1.000											
4. Gender	0.091***	0.042***	-0.042***	1.000										
5. Age	0.092***	-0.095***	-0.094***	0.138***	1.000									
6. Yrs in Education	0.013**	-0.160***	-0.151***	0.030***	0.068***	1.000								
7. Legislators/Senior Officials/Man.	0.023***	-0.015***	-0.030***	0.124***	0.061***	0.096***	1.000							
8. Professionals	0.012**	-0.158***	-0.145***	0.075***	0.111***	0.608***	-0.144***	1.000						
9. Techn./Assoc. Profess.	-0.025***	-0.020***	-0.005	-0.153***	-0.037***	-0.034***	-0.156***	-0.293***	1.000					
10. Clerks	-0.036***	0.015***	0.019***	-0.180***	-0.043***	-0.091***	-0.101***	-0.190***	-0.205***	1.000				
11. Service/Sales Workers	0.006	0.003	0.053***	-0.209***	-0.087***	-0.189***	-0.094***	-0.176***	-0.191***	-0.124***	1.000			
12. Agric./Fish./Craft/Trade Workers	0.016***	0.122***	0.068***	0.284***	-0.026***	-0.231***	-0.107***	-0.201***	-0.217***	-0.141***	-0.131***	1.000		
13. Plant/Machine Oper./Assemblers	0.020***	0.092***	0.059***	0.161***	0.015***	-0.192***	-0.071***	-0.133***	-0.144***	-0.093***	-0.087***	-0.099***	1.000	
14. Elementary Occupations	-0.003	0.032***	0.041***	-0.041***	-0.000	-0.199***	-0.072***	-0.136***	-0.147***	-0.095***	-0.089***	-0.101***	-0.067***	1.000

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 31: Test for Multicollinearity – VIF

Variable	VIF
Job Insecurity	1.14
Job Insecurity Partner	1.13
Gender	1.05
Age	1.04
Yrs in Education	1.45
ISCO-Code 88 (continuous)	1.46
Mean VIF	1.21
Job Insecurity	1.15
Job Insecurity Partner	1.13
Gender	1.27
Age	1.05
Yrs in Education	1.85
Legislators/Senior Officials/Managers	2.14
Professionals	4.60
Techn./Assoc. Profess.	3.79
Clerks	2.57
Service/Sales Workers	2.38
Agric./Fishery/Craft/Trade Workers	2.76
Plant/Machine Operators/Assemblers	1.89
Mean VIF	2.21

Note: VIF calculation after linear regression. DV: MCS.

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