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Modelling the Dynamics of Vulnerability with Latent Variable Methods

THÈSE

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prof. Gilbert Ritschard

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La Faculté des sciences de la société, sur préavis du jury, a autorisé l'impression de la présente thèse, sans entendre, par-là, émettre aucune opinion sur les propositions qui s'y trouvent énoncées et qui n'engagent que la responsabilité de leur auteur.

Genève, le 9 décembre 2020

Le doyen
Bernard DEBARBIEUX

Impression d'après le manuscrit de l'auteur
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Abstract

The 2008 Financial Crisis and the Great Recession, precipitated by the bursting of the US housing bubble, led to one of the worst economic downturns since the Great Depression.[1] The consequences of the crisis and ensuing recession were varied and substantial. Most countries in the Western world experienced sharp declines in their GDP. Unemployment, particularly in the US, Greece, Spain, Portugal, and Italy, increased dramatically. Even while the economy began to recover, the unemployment rate decreased slowly and took nearly ten years to reach pre-crisis levels in OECD countries. Income and wealth inequality also continued to rise to unprecedented levels in the US but less so in Europe. However, most of the focus has been on the consequences of the crisis at the aggregate level. Instead, this thesis will investigate labour market consequences at the individual level in a vulnerability perspective.

Vulnerability here is conceived as a process which occurs after an individual is exposed to a source of stress, such as an unexpected event, in a given context. The vulnerability process is a consequence of individuals not having the necessary resources to prevent the occurrence of negative consequences for their lives, not being able to cope with, or minimize the effects of, these negative consequences, and potentially being unable to recover from the negative consequences.

The aim of this thesis is to apply and model this vulnerability process. It proposes the use of two types of latent variable models: latent growth curve models, and latent class models. These two types of latent variable models can be used to investigate the vulnerability process as a whole while certain variants of latent class models can also be used to model transitions between different parts of the vulnerability process. A particular focus will be put on using these methods to model vulnerability when the negative consequences are measured using categorical variables. The application of these methods to the vulnerability process framework will be illustrated using panel data from the UK and Switzerland to investigate the consequences of the 2008 Financial Crisis relative to unemployment and precarious employment.

The results of these applications show the importance of taking into account context in the analysis of vulnerability. Despite individuals in the UK and Switzerland being exposed to the same source of stress, the 2008 Financial Crisis, there are substantial differences in labour market outcomes. Women for instance were less likely to become unemployed during the Great Recession than men in the UK while this is not the case in Switzerland. Educational differences were more pronounced in the UK but less apparent in Switzerland in relation to unemployment. As for precarious employment, women were more likely to have more unstable jobs than men after the crisis in Switzerland but became less likely to have such positions in the UK. In Switzerland, unlike the UK, highly educated individuals became more likely to be in precarious employment following the crisis.

1. However, at the time of writing, the COVID-19 pandemic looks like it has the potential set off a crisis even worse than the Great Recession or even the Great Depression.

Résumé

La Crise Financière de 2008 et la Grande Récession, précipitées par la fin de la bulle immobilière aux États-Unis, ont mené à un des plus grands ralentissements économiques depuis la Grande Dépression.[2] Les conséquences de cette crise et de la récession qui a suivi ont été variées et considérables. La plupart des pays occidentaux ont expérimenté des déclins marqués de leur PIB. Le chômage, surtout aux USA, la Grèce, l'Espagne, le Portugal et l'Italie, a augmenté de manière dramatique. Même durant la reprise économique, le taux de chômage a baissé lentement et a pris presque dix ans pour revenir au niveau de l'avant-crise dans les pays de l'OCDE. Les inégalités de revenu et de fortune ont continué de croître à des niveaux jamais vus aux USA, mais c'était moins le cas en Europe. Toutefois, l'accent a été mis surtout sur les conséquences de la crise au niveau macro. La présente thèse par contre, va d'étudier les conséquences liées à l'emploi au niveau individuel dans une perspective de vulnérabilité.

La vulnérabilité ici est considérée comme un processus qui a lieu après l'exposition d'un individu à une source de stress, par exemple un évènement inattendu, dans un contexte donné. Le processus de vulnérabilité est une conséquence du fait que des individus n'ont pas les ressources nécessaires pour empêcher des conséquences négatives pour leurs vies, ne peuvent pas faire face à, ou minimiser l'effet de, ces conséquences négatives et potentiellement n'arrivent pas à se remettre de conséquences négatives.

Le but de la présente thèse est d'appliquer et modéliser ce processus de vulnérabilité. Elle propose l'utilisation de deux types de modèles à variables latentes : les courbes de croissance latente et les modèles de classes latentes. Ces deux types de modèles à variables latentes peuvent être utilisés pour analyser des trajectoires entières ou alors que certaines variantes de modèles à classes latentes peuvent aussi être utilisées pour modéliser des transitions entre différentes parties du processus de vulnérabilité. Un accent sera mis particulièrement sur l'utilisation de ces méthodes pour modéliser la vulnérabilité quand les conséquences négatives sont mesurées avec des variables catégorielles. L'application de ces méthodes au cadre de la vulnérabilité va être illustrée avec des données de panel du Royaume-Uni et de la Suisse pour analyser les conséquences de la Crise Financière de 2008 relatives au chômage et l'emploi précaire.

Les résultats des applications montrent l'importance de prendre en compte le contexte dans l'analyse de la vulnérabilité. Malgré le fait que les individus au Royaume-Uni et en Suisse ont été exposés à la même source de stress, la Crise Financière de 2008, il y a des différences marquées en ce qui concerne les conséquences liées au marché du travail. Les femmes, par exemple, avaient moins de chances de se retrouver au chômage en comparaison avec les hommes au Royaume-Uni alors que ce n'est pas le cas en Suisse. Les différences de niveau de formation étaient plus prononcées au Royaume-Uni, mais moins marquées

2. Mais, au moment de la rédaction de la présente thèse, la pandémie COVID-19 semble avoir le potentiel de déclencher une crise encore pire que la Grande Récession ou même la Grande Dépression.

en Suisse quant au chômage. En ce qui concerne l'emploi précaire, les femmes avaient plus de chances d'avoir un travail instable que les hommes en Suisse après la crise, mais au Royaume-Uni ces chances ont diminué à la suite de la crise. En Suisse, contrairement au Royaume-Uni, les individus avec un haut niveau de formation sont devenus plus susceptibles d'avoir un emploi précaire à la suite de la crise.

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Chapter 1 Introduction

Operationalizing Vulnerability

The concept of vulnerability has seen its use increase and spread in recent times. However, its origin and use vary substantially in different disciplines. In the case of the social sciences, it is argued by Füssel (2007) and Misztal (2011) that vulnerability grew in use due to the popularity and development of the concept in the environmental sciences. Nevertheless, similar concepts such as risk and social exclusion which appeared earlier in the social sciences share much with the vulnerability perspective in the environmental sciences. In addition, the work on social stress (Aneshensel 1992; Kessler 1979; Turner and Noh 1983; Kessler and McLeod 1984; Kessler et al. 1985) and the stress process model (Pearlin 1989; Pearlin et al. 1981) also has many commonalities with the concept of vulnerability in use by the environmental sciences.

However, there seems to have been a convergence towards a common foundation, especially in the environmental sciences, on which most definitions of vulnerability are built even if differences persist between and within disciplines. Broadly speaking, vulnerability is conceived as being the degree to which individuals, or households, communities, etc., are likely to experience harm or negative consequences when exposed to a hazard or source of stress. While definitions of this type encompass many aspects of vulnerability, what hazards and sources of stress are, and what constitutes harm or negative consequences often differs between disciplines.

In the environmental sciences, much of the focus is on natural hazards and the consequences for people's livelihoods. In the social sciences, a large part of the focus is on events such as job loss, the school-to-work transition, bereavement, or divorce. The main difficulty in the social sciences is that, in most cases, the hazards or stressors faced by individuals are not strictly exogenous. The chances of being exposed to sources of stress, especially those that are socially produced, is not necessarily equal among all individuals and this needs to be taken into account when studying vulnerability.

The negative consequences that are studied also vary by discipline. In psychology, but also work on social stress, most of the focus is on mental health or depression. In other social sciences, for instance sociology, negative consequences such as poverty, social exclusion, or a decline in well-being are quite often studied. The scale of analysis also varies substantially between different disciplines. The social and psychological sciences focus more on the individual or household level. The environmental sciences, on the other hand, often analyse vulnerability at a larger scale such as the community, regional, or even planetary level.

In this thesis, the concept of vulnerability follows the dynamic framework proposed by Spini et al. (2013) and Spini et al. (2017). In this framework, vulnerability is defined as a lack of resources which puts individuals at risk of experiencing negative consequences when exposed to a stressor, and which potentially prevents them from coping with, and recovering from, these negative consequences. What this framework adds to more general definitions of vulnerability is a more explicit time dimension and shows that vulnerability is, in a sense, a process. The lack of resources can be punctual, but more often than not is the result of social processes determining what individuals will have at their disposal to deal with unexpected events or sources of stress.

While this definition is somewhat more precise than the broad, shared, definition of vulnerability common in the environmental sciences, it nevertheless poses various methodological challenges regarding its operationalization. The different chances of being exposed to a source of stress need to be taken into account especially in the case of stressors that are socially produced. Resources also need to be measured as well. They can be of different types, Spini et al. (2013) and Spini et al. (2017) for instance distinguish between biological, psychological, and social resources, and they can be measured with multiple indicators. Therefore, for a more complete picture, a multidimensional approach to measuring resources can be useful.

Then there are the elements of the process: negative consequences, coping and recovery. To model processes such as these, we need to observe individuals over time and this requires longitudinal data and methods. Additionally, in the study of vulnerability, understanding differences in the consequences *between* individuals when exposed to sources of stress is of major interest. Another aspect that can potentially introduce difficulties in modelling processes of vulnerability is that the negative consequences can be multidimensional. For instance, in the case of losing one's job, the consequences can be financial, for example making individuals more likely to experience poverty, as well as psychological by decreasing individuals' well-being and increasing their risk of depression (Pearlin 1989; Spini et al. 2017).

Where this thesis aims to expand on the work of vulnerability is through the analysis of outcomes which when observed are measured as categorical variables. In the social sciences, where many outcomes cannot be easily measured through continuous scales or constructs, more specific methods, or extensions of existing methods are required. In addition, there are different methods required depending on how the underlying measure of vulnerability is conceived; considering the underlying measure of vulnerability as continuous is not the same as considering it as being categorical. Moreover, this choice also affects *how* the results of an analysis of vulnerability are interpreted and provide answers to potentially different questions. This aspect of investigating noncontinous outcomes adds further complexity to the existing challenges of modelling vulnerability especially in conjunction with longitudinal and multidimensional data.

Methods

In order to be able to take into account these requirements, in this thesis, the use of latent variable models is proposed to study vulnerability. Latent variable models are a general class of statistical model designed, principally, to model constructs that are not directly observed or which are *latent*. The use of latent variable models is particularly relevant in the case of multidimensional constructs. In this thesis, two specific latent variable models are used: latent growth curve modelling and latent class analysis.

Latent growth curve modelling is an approach where change over time is thought to follow an unobserved latent process (Bollen and Curran 2006; McArdle and Nesselroade 2014; Grimm, Ram, and Estabrook 2017). These models can be considered as a special case of a specific class of latent variable model: confirmatory factor analysis (Meredith and Tisak 1990). Growth curve models allow for modelling processes over time by considering that there are latent, unobserved, variables that can explain patterns of change in an outcome over time. Using latent variables, it is possible to specify the functional form of change over time. This can be modelled in a relatively simple manner as a linear function, but also in more complex manners with quadratic or cubic functions, or the use of spline functions allowing for linear change to be broken up into different parts. Growth curve models also allow for taking into account unobserved differences between individuals, also referred to as unobserved heterogeneity, in relation to the overall general trajectories estimated. Furthermore, covariates can be included in these models to further investigate differences between individual trajectories of vulnerability in relation to observed, or manifest, variables such as age, or gender.

Moreover, growth curve models, by virtue of being latent variable models, also allow for integrating multidimensional constructs measuring vulnerability, or resources. They can be further extended to potentially model multiple processes of vulnerability simultaneously and analyse potential interconnections between them. These models are best suited to analysing continuous variables, whether they are manifest or observed, in situations where change over time is considered to be continuous or instantaneous. Work on developing latent variable models has also allowed the incorporation of manifest categorical variables as the dependent variables. It is on this development that this thesis focuses on in order to illustrate the application of the vulnerability framework.

The analysis of vulnerability, especially in the psychological sciences, most often focuses on continuous outcomes or scales. Nevertheless, many outcomes in the social sciences when measured or observed are discrete, i.e. categorical, but can be thought of measuring an underlying *continuous* latent or unobserved construct. This latent construct can be conceived as measuring the individual *propensity* for an outcome to occur and this propensity itself can be considered as a continuous scale. Therefore, the use of latent growth curve models with categorical outcomes offers a method for investigating and understanding vulnerability with observed noncontinuous outcomes. In addition, most, if not all, developments of latent growth curve models can be applied with noncontinuous outcomes making it an extremely flexible method and a good choice for investigating the vulnerability process potentially over a very long period of time.

Latent class models are another special case of latent variable models slightly more suited to analysing manifest categorical variables (Collins and Lanza 2010; Bartholomew et al. 2011; McCutcheon 2002). Because latent class models are also latent variable models, they can also model multidimensional concepts similarly to factor analysis models. Where they differ is that the underlying latent variables are considered to be categorical rather than continuous. Initially latent class models were developed for the analysis of cross-sectional data, but they can also be used to model longitudinal data (Collins and Lanza 2010, 181). The longitudinal of variant of latent class models can be used to classify individuals into different categories of trajectories based on their responses to a set of observed categorical variables over time. It is also possible to incorporate explanatory variables to analyse differences between individuals for instance in relation to the resources at their disposal.

Another approach to using latent class models in a longitudinal context is latent transitions analysis (LTA) (Collins and Lanza 2010, 187). Rather than taking a holistic approach and modelling entire trajectories, the focus of LTA is movements, or transitions, between different states or positions in a trajectory. In the study of vulnerability, this approach could for instance be used to analyse transitions between stages of the vulnerability process such as between coping and recovery. It is also possible to incorporate explanatory variables that can be used to investigate differences between individuals in the chances of transitioning between different stages of vulnerability trajectories. LTA models can be implemented using joint models which estimate the latent classes and the transitions simultaneously. Another possibility is to estimate the latent classes first and then estimate the transitions using dynamic panel models for categorical outcomes (Heckman 1981a, 1981b; Wooldridge 2005). Joint estimation methods become very complex as the number of time points increases (Collins and Lanza 2010, 189) and that is why, in this thesis, a new method of for estimating an LTA models without using a joint model is proposed in Chapter 6.

Another possibility offered by latent variable models is another way of specifying and understanding standard regression models for categorical variables such as the logistic and probit regressions. Doing so allows for developing methods that allow for testing mediation when the outcome is noncontinuous as it provides a better understanding of the relationship between the underlying latent model and the estimated model. In the case of mediation models, considering noncontinuous regression models as latent variable models allows for understanding why the properties of mediation models with linear outcomes don't hold in the case of noncontinuous outcomes. This also allows for establishing solutions to this problem such as those proposed by Karlson et al. (2012), Wooldridge (2010), or Winship and Mare (1984). In the study of vulnerability, this is a useful tool as it allows for analysing the potential mediating effects of certain contextual factors, or resources on other resources with categorical outcomes. In other words, in the case of categorical variables measuring negative consequences, it would be possible to analyse to which degree differences in the observed effects of resources are explained by other resources, or by context.

Applications: Labour Market Outcomes after the 2008 Financial Crisis

The 2008 Financial Crisis and the subsequent Great Recession were among the biggest economic disruptions since the Great Depression(Grusky et al. 2011)[1]. The crisis was set off by a decline in housing prices in the US, but spread worldwide due to the development of, and substantial investment in, risky but profitable financial instruments by banks based outside the US (Fligstein and Habinek 2014; Pernell-Gallagher 2015). This crisis led to a substantial decline in GDP for most countries

1. However, the economic downturn in the wake of the COVID-19 pandemic is, or will be, more pronounced (Ahmed et al. 2020).

in the Western world.

The consequences were wide-ranging. The unemployment rate in most OECD countries increased substantially (Keeley and Love 2010) and recovered relatively slowly (Redbird and Grusky 2016; OECD 2018). Youth unemployment, particularly in Southern Europe, increased dramatically. In Europe, the 2008 Financial Crisis provoked sovereign debt crises in Greece, Ireland, Italy, Portugal, and Spain which subsequently led to the implementation of severe austerity measures. Increases in poverty were more moderate and varied substantially between countries with those implementing austerity measures being the most affected. Income inequality, already rising prior to the crisis, continued to increase in the US after the crisis. This, however, was not the case in Europe where income inequality remained relatively flat, and in some cases decreased. However, increases in wealth inequality were generally more pronounced and more widespread. The crisis also had consequences for health particularly in Greece and Spain, but also for mental health in general especially among the unemployed. However, this previous work on the consequences of the crisis in relation to labour market consequences principally focuses on aggregate-level dynamics. In this thesis, the emphasis is on individual-level dynamics relative to labour market outcomes in a vulnerability perspective.

In the applications employing the vulnerability framework, a particular focus will be placed on differences in individual trajectories of unemployment following the crisis as well as transitions to and from precarious employment. Using longitudinal data from the Swiss Household Panel, the British Household Panel, and Understanding Society: The UK Household Longitudinal Study, the applications model and compare trajectories of unemployment and transitions to vulnerable employment between the UK and Switzerland to understand the role of different contexts in addition to individual resources in relation to vulnerability.

Contribution of the Thesis

In sum, this thesis offers insight into the difficulties in defining and operationalizing vulnerability through the implementation of the LIVES (Spini et al. 2013; Spini et al. 2017) vulnerability framework. Where it adds to existing research is the exploration of how to best link vulnerability frameworks with modelling approaches, and the analysis and interpretation of results when investigating categorical outcomes using longitudinal data to study vulnerability. It also contributes to the work on vulnerability by disentangling the elements that comprise a vulnerability framework, notably the distinction between risk, or exposure, and vulnerability. It discusses the multidimensional nature of vulnerability and resources, as well as the necessity to look at change over time as vulnerability is, after all, a process of dealing with sources of stress. It also discusses how the results of the methods applied, most notably latent growth curve models and latent class analysis, can be interpreted and linked to the theoretical constructs proposed in the LIVES vulnerability framework. It thus seeks to more closely link existing methods and the specificities of the analysis of vulnerability.

This thesis also demonstrates the particularities of modelling vulnerability with latent constructs derived from observed categorical data while providing an illustration and investigation of the effects of the 2008 Financial Crisis on labour market outcomes in different contexts. It notably shows that the methods chosen for the analysis of vulnerability influence *how* vulnerability is conceived and analysed especially in relation to outcomes that are not measured on continuous scales. Different methods have different assumptions about the form of the underlying latent measure of vulnerability. Notably, through the applications in Chapters 6 and 7, it shows the different possibilities available for modelling longitudinal processes with latent variable models and categorical outcomes. It also applies and combines methods to overcome difficulties presented by certain statistical frameworks, notably latent transition analysis, in using complex latent variable models with intensive longitudinal data. Finally, it also discusses the difficulties and challenges associated with creating a complete and exhaustive model of vulnerability and the limitations of the applications presented here in relation to the exposure–vulnerability relationship as well as the possibility of answering even more complex questions using the methods presented here.

Structure of the Thesis

The structure of the thesis is as follows: in Chapter 2, there will be an overview of the 2008 Financial Crisis. Its causes and its consequences, in particular for the US and Europe, will be discussed. In terms of the consequences of the crisis, particular attention will be paid to labour market outcomes, inequality and poverty, and health outcomes.

In Chapter 3, the concept of vulnerability and a dynamic perspective for the analysis of vulnerability will be presented. More specifically, the concept of vulnerability will be examined in relation to the different definitions of the concept present in the environmental and social (principally sociology and psychology) sciences. Vulnerability will also be contrasted and compared to other closely related notions such as risk or resilience. A consistent terminology will be introduced before a vulnerability framework drawing on Spini et al. (2013) and Spini et al. (2017) is described and linked to labour market outcomes in the aftermath of the financial crisis. More specifically, the relationship between risk, vulnerability, and negative outcomes will be defined in relation to trajectories of vulnerability. The role of resources and conceptual issues related to their measurement will also be discussed and the importance of taking into account contextual elements will also be explored.

In Chapter 4, latent variable methods for modelling vulnerability will be presented. After discussing the estimation of latent variable models within the structural equation modelling framework, longitudinal latent growth curve models will be presented. Issues relating to model specification and interpretation in relation to the vulnerability framework established in Chapter 3 will be addressed. Subsequently, latent class models, and their longitudinal extensions, will also be explored and discussed in relation to growth curve models. The differences between the two types of models in relation to modelling vulnerability will also be studied. Dynamic panel data models, which will be combined with latent class models, will also be presented.

In Chapter 5, mediation models for noncontinuous outcomes in latent variable perspective will be described and three potential solutions presented. Our implementation of an innovative method created by Karlson et al. (2012) as an R package will be described. The method will be illustrated using a discrete-time survival analysis looking at the risk of unemployment in Switzerland following the 2008 Financial Crisis. The usage of the package will be illustrated in more detail by an example investigating educational achievement in relation to parental socioeconomic position and results will be compared with the existing Stata implementation of the method (Kohler et al. 2011).

In Chapter 6, latent growth curve models will be used to model trajectories of vulnerability in relation to unemployment following the 2008 Financial Crisis. Individual trajectories will be compared according to sociodemographic characteristics. Differences in trajectories between the UK and Switzerland will also be investigated.

In Chapter 7, latent class models are combined with dynamic panel models to analyse employment transitions following the crisis. The focus is on investigating the potential for the crisis to make individuals more likely to enter insecure forms of employment. As in Chapter 6, individual differences will be explored and the UK and Switzerland will be compared as well.

These applications serve to illustrate two different approaches to modelling vulnerability using noncontinuous outcomes in a longitudinal approach and in relation to the vulnerability framework presented in Section 3.3. They also show that these two approaches do not model vulnerability in the same way as in one case vulnerability is treated as a continuous underlying latent variable rather than a categorical one in the other case. These applications also demonstrate *how* the methods presented, latent growth curve models and latent transition models, differ and the potential difficulties associated with them. In the case of latent transition analysis, the application in Chapter 7 also demonstrates a novel method for estimating an LTA model, or one very close to it, in a situation where many time points are required which is not always feasible with standard implementations of the method.

Finally, in the conclusion the results of the applications in Chapters 6 and 7 are discussed in relation to aggregate-level labour market trends in the aftermath of the 2008 Financial Crisis. The advantages and potential limitations of modelling vulnerability with latent growth curve and latent class models are also discussed using the applications as examples. Lastly, directions for further research in modelling vulnerability are proposed principally in relation to the multidimensionality of the process, outcomes and resources, and differences in the chances of exposure to sources of stress.

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Chapter 2 The 2008 Financial Crisis and the Great Recession

The 2008 Financial Crisis and the subsequent Great Recession, considered to be the biggest economic downturn since the Great Depression, are among the critical events of the early 21st century. While the crisis originated in the US, it subsequently spread to almost all of the Western world in a very short amount of time. It had wide-reaching consequences not only for countries' financial sectors, but also their labour markets, governments, and households. The crisis can be considered as one of the most significant socially produced sources of stress in recent times, and one of its distinguishing factors is that it almost all individuals regardless of their social status or position were exposed to it. Consequently, it becomes an interesting case to examine within the vulnerability framework as will be presented in Section 3. This chapter will cover the origins of the crisis and the subsequent recession, the consequences for the labour market, and other domains such as health, in European countries in particular before concluding.

2.1 Origins

The origins of the 2008 Financial Crisis and the ensuing Great Recession can be found in the sub-prime mortgage crisis in the US (Reinhart and Rogoff 2011, 208). There is still debate on what in particular triggered the crisis. Already in 2007, there were signs of an unsustainable housing bubble and an increasing risk of default in relation to sub-prime mortgages. The focus on sub-prime mortgages is, in a sense, a short-term view of the origins of the crisis as it focuses principally on policy and regulatory changes made in the 10 to 15 years prior to the crisis itself.

In the US, two government-backed entities Fannie Mae and Freddie Mac were founded as institutions to buy mortgages in the secondary market. However, these institutions became increasingly central in the mortgage market with the introduction of a bill setting targets for purchasing mortgages from low-income and minority housing regions by the Department of Housing and Urban Development (HUD) (Wallison 2009; Thompson 2009; Friedman 2010). This pushed these two institutions to purchase an increasing amount of sub-prime mortgages to meet targets set for financing mortgages of low-income households who traditionally faced more barriers to home ownership. While Fannie Mae and Freddie Mac officially didn't issue mortgages to low-income households, they were among the largest purchasers of such mortgages as well as subprime mortgages in general (Campbell 2010, 375), often through mortgage-backed securities. At the time of the crisis, these two institutions alone guaranteed approximately 40 percent of all subprime mortgages (Wallison 2010).

Nevertheless, others (Krugman 2008, 163; Aalbers 2009; Comiskey and Madhogarhia 2009, 272–273; Stiglitz 2010a, 10; Avery and Brevoort 2015) contend that the role in the subprime crisis played by Fannie Mae and Freddie Mac, and government policies encouraging home ownership among lower-income households, is overstated and that the housing bubble wasn't related to government policies. Rather, increasing housing prices and speculation artificially gave higher returns on financial derivatives and encouraged increasingly lax mortgage policies on the part of lenders. Some homeowners were actually encouraged to borrow repeatedly against their homes – "to treat their houses as ATMs" (Stiglitz 2010a, 78) – as during the bubble, the value of housing continually increased. Moreover, loans under government programmes such as the Community Reinvestment Act (CRA) which were supposed help low-income households buy homes, had to be provided by banks while the majority of subprime loans were provided by non-bank lenders (Aalbers 2009, 348).

While this policy of encouraging home ownership among lower-income households usually considered too risky to receive mortgages may have been a contributing factor, the choice to invest in the US housing market in the aftermath of the dot-com bubble is another aspect that needs to be considered. The end of the dot-com bubble brought a substantial decrease in interest rates in order to counteract a potential recession (Gjerstad and Smith 2010). This coupled with another policy change, the Taxpayer Relief Act which partially exempted housing assets from capital-gains tax, further encouraged investment in the housing sector. Some argued, particularly Ben Bernanke former chair of the Federal Reserve, that investment in the US housing market was further spurred by a "global savings glut" (Reinhart and Rogoff 2011, 209; Elson 2017, 118; McCauley 2019) which favoured more investment in the US economy and provided cheap credit and loans to support a growing housing bubble. There is nevertheless evidence which suggests that this savings glut was in fact not particularly pronounced (Taylor 2010).

In fact, McCauley (2019) argues that it wasn't a savings glut that contributed to the crisis but rather a "banking glut", especially on the part of European banks, that contributed to the crisis. McCauley finds that European banks overwhelmingly invested in the mortgage-backed securities of US banks. This sent a signal encouraging financial institutions in the US to provide more mortgages to more "risky" households to satisfy the growing demand for mortgage-backed securities which essentially comprised sub-prime mortgages. There is even evidence that banks, and European banks in particular, invested in collateralized debt obligations (CDOs) and other financial derivatives in the hopes of being more competitive and profitable relative to American banks even when there was no clear evidence that investing in these instruments increased profitability (Acharya and Richardson 2010; White 2010; Fligstein and Habinek 2014; Pernell-Gallagher 2015; McCauley 2019).

In addition to an increasing amount of potential risky loans and mortgages being made all while housing prices continued to increase, another contributing factor is that it is precisely this risk that was being obscured with the use of new financial tools, and more particularly the proliferation of derivatives. These financial derivatives, which were presented as a manner to absorb potential investment risks were often misrepresented, and the effective risk of default underestimated (Stiglitz 2010b; White 2010; Brancaccio and Fontana 2011; Elson 2017). In part, banks abused the "originate to distribute" model of providing mortgages where they would provide households with mortgages with little regard for the ability of the beneficiaries to pay them off or deal with potential market changes as they were no longer responsible for the mortgage (Baker 2010; Martin 2011, 595; Elson 2017, 27). Every intermediary in this model of lending makes a profit through transaction fees when selling on the mortgage to another institution to be packaged into financial derivatives. This therefore provided few incentives to the first institution in the chain providing the mortgage – the originator – to actually verify whether the borrower could repay the loan (Acharya et al. 2009, 105).

In fact, banks increasingly pushed for the use of mortgage-backed securities and other forms of CDOs as it seemed that such financial instruments performed better and led to more profits than more traditional (and secure) forms of investment (Acharya and Richardson 2010; White 2010; Pernell-Gallagher 2015). This coupled with rating agencies having an incentive to rate financial instruments in accordance with banks' wishes led to financial instruments and securities being considered safer than they were in reality (Comiskey and Madhogarhia 2009, 272; Crotty 2009, 566; Stiglitz 2010a, 7; White 2010, 235; Elson 2017, 28).

While the crisis was presented as being "unexpected" (Stiglitz 2010a, 1; Martin 2011, 587–588; Elson 2017, 45), there is a line of argument that considers the 2008 Financial Crisis to be evidence of an unsustainable model of economic growth and places the origins of the crisis much further back in time. The transformation and financialization of economic systems, and the rise of neoliberalism, reduced guarantees for individuals and promoted a shift away from income security. Consequently, households' wealth became increasingly related to the ownership of housing and the necessity of finding investment opportunities for those with disposable income to invest led to a succession of bubbles, with the most recent being the dot-com and pre-crisis housing bubbles.

This line of thought places the origins of the 2008 Financial Crisis far further in the past than earlier accounts did. Rather than focusing on the United States government's policies concerning lending and easy access to credit to encourage home ownership, this crisis is viewed as a consequence of a long-term trend in the erosion of individuals' income and growing inequality (Appelbaum 2011; Piketty and Saez 2014).

Wisman (2013) argues that there are three long-term driving forces behind the crisis. The first is the decline in investment in the real economy. As households who would spend most of their income on consumption saw their incomes drop compared to richer households, the economy increasingly relied on speculative investments such as the stock market (as evidenced with the dot-com bubble) and then real estate. Wisman further argues that this was exacerbated by wages not increasing in line with productivity. Thus, households who spend most of their income on consumption saw their relative purchasing power compared to richer households decline while business owners saw their earnings increase. Tridico (2012) also contends that for investors to see increasing dividends with levels of economic growth that were not much greater than during the height of the Fordist era, wages needed to be compressed so that large investors could make a return on their investments.

The second element, also related to the relative decline of incomes and increasing inequality, is the growing need for households to find other ways in which to meet their needs and relative status (Elson 2017, 36), either through reducing savings, working longer hours, or taking on more loans. This is incredibly striking in the US as while per capita income (adjusted for inflation) increased over time, the increase for the bottom 90 percent of households was much less pronounced. Moreover, the increase was strongest among the top one percent of households (Wisman 2013). Taking shares of income, Redbird and Grusky (2016) show that for all but the top two quintiles, the share of income (relative to 1967) declined over time and was the worst for the lowest quintiles. A corollary of this decline in wages is that to sustain similar levels of consumption, the financial system would have to facilitate access to loans for households. Consequently, consumption was sustained not by wages and the real economy, but by a number of financial instruments designed to close the gap between needs and available income (Campbell 2010, 374; Tridico 2012).

The third element refers to "regulatory capture" or the increasing influence of the rich on policies that would favour their economic situation. This in turn led to legal changes which cut taxes for the highest wealth and income brackets, deregulated the financial sector, prevented the regulation of financial instruments, and reduced social spending. These changes allowed, and even encouraged, firms and households to take on more debt as borrowing became cheaper. Public debt was replaced over time by an ever-increasing amount of private debt (Streeck 2011). Increasingly, banks and financial institutions steered governments to adopt policies that served their own interests and even managed to present them as policies that would serve the greater good partially by relying on economic theories that supported their cause (Stiglitz 2010b; Baker 2010). Regulatory capture was especially pronounced in Anglo-Saxon countries – the US and the UK – and was helped by comparatively lax rules concerning lobbying, and/or campaign funding. In fact, Fannie Mae and Freddie Mac which should have been under far more scrutiny than most commercial banks, engaged in extremely risky, and sometimes illegal practices, despite obligations to invest in more secure mortgages (Thompson 2009; Elson 2017, 27).

An extension of regulatory capture is the proliferation and expansion of the shadow banking system. The repeal of the Glass-Stegall Act, which served to separate commercial and investment banking in the US, allowed all banks to find new ways in which to raise capital and therefore encouraged the development and spread of the shadow banking system (Campbell 2010, 379). Financial derivatives instead of being traded on open markets, like stocks, were traded directly between institutions and were mostly exempt from any sort of government regulation or oversight (Krugman 2008, 163; Crotty 2009; Elson 2017, 224). The apparent lack of regulation was in part linked to arguments made by institutions and economists stating that regulation wasn't necessary as the markets would correctly price financial instruments in relation to their risk and their expected return. In fact, the US government almost openly intervened to prevent any efforts to regulate the shadow banking system and even subprime mortgages (Krugman 2008, 164). Moreover, the rise of the shadow banking system was related to changes to banking regulations which allowed *all* banks to hold risky assets off book without any capital requirements which would thus encourage them to transfer as many assets as they could into unregulated entities which they controlled.

Consequently, while the immediate cause of the 2008 Financial Crisis and the subsequent recession would seem to be related to the property bubble in the US, it is long-term trends in financial deregulation, growing wealth and income inequality, overinvestment and overconfidence in the US housing market, and new financial instruments that kicked off the series of events leading to the near-collapse of the financial sector not only in the US but worldwide. The first signs of potential problems in the financial sector began to rear their heads in 2007 (Krugman 2008, 168; Chodorow-Reich 2014; Fligstein and Habinek 2014). The rescue of hedge funds highly invested in subprime mortgages in June 2007 by Bear Stearns was any early warning as was BNP Paribas' freezing of similar investment funds. There was a short-term increase in the interbank lending rate, and subsequently Bear Stearns was forced to sell itself to J.P. Morgan. The situation seemed to stabilize until September 2008 when Lehman Brothers went bankrupt as the interbank lending rate rose sharply and banks effectively couldn't borrow any money.

In the wake of the end of the housing bubble, the assets held by institutions in the shadow banking system lost value and investors sought to pull out. In part the opacity of financial derivatives packaging multiple types of debt exacerbated the issue as investors couldn't figure out which debts actually backed a CDO, or a mortgage-backed security (MBS). Investors then proceeded to sell off all derivatives in an effort to avoid major losses further depressing their value. To cover the shortfall, some financial institutions turned to bank loans, but the interest rates were on the rise and access to credit was becoming more difficult.

However, the crisis wasn't only contained to investment banks. The world's largest insurance firm AIG had to be bailed out by the government as it had got very involved in the derivatives market by insuring holders of derivatives such as CDOs or MBSs from potential losses using a new form of derivative called a credit default swap (CDS). However, there were no capital requirements for holding CDSs which meant that there was no effective way to ensure that a holder of CDS would be able to receive any compensation in the case of a default. This led to the collapse of AIG and the US government effectively had to bail it out (Chodorow-Reich 2014).

Thus, what was initially the end of a real-estate bubble led to not only the collapse of the banking sector in the US, but also spread to the rest of the world in a short amount of time, seemingly ignoring borders. The spread of the crisis from the US to the rest of the world is related to numerous mechanisms. The first is simply the high level of investment in the US securities market by banks outside of the US, particularly those in Europe (Stiglitz 2010a, 21). Fligstein and Habinek (2014) show that countries with high levels of investment in US MBSs were more likely to have experienced a systemic banking crisis in the aftermath of the US housing bubble bursting. However, they find no evidence that other aspects such as a domestic housing bubble, financial deregulation, a high level of exports to the US, or even government debt had any association with the likelihood of countries experiencing a banking crisis.

Another mechanism for the spread of the crisis is related to cross-country loans. In certain cases, banks – and households – would take loans in countries where the interest rate was lower and then provide loans in countries where the interest rate was comparatively high. The collapse of Lehmann Brothers, which was unexpected as the market assumed that its assets would be protected, caused a panic and destroyed market confidence. This then led to a decline in credit availability and for countries with low interest rates an appreciation of their currency, while for countries borrowing from low interest rate countries, the depreciation of their currency. So even in countries where banks and financial institutions hadn't directly invested, or invested to a lesser degree, in US financial derivatives, the effect of the banking crisis in the aftermath of the drop of housing prices in the US continued to affect may other countries (Krugman 2008, 180).

Finally, many economies rely on the US and export massively to it, particularly Asia and Europe. When a crisis hits, consumption is one of the first things to decline and was especially pronounced in countries where consumption is debt-driven (Mian and Sufi 2010), and countries whose economic growth is highly linked to the US economy saw their own levels of growth decline (Stiglitz 2010a, 21). With the US consuming less, countries with export-dominated markets saw one of their major sources of income decline, in addition to whatever other avenues of involvement in the US economy had managed to affect their economies, further compounding economic decline.

2.2 Consequences

The consequences of the crisis were wide-ranging. The first was the more or less complete collapse and subsequent disappearance of the entire derivatives market and the institutions that were involved in it (Fligstein and Habinek 2014, 661). The most immediate consequence was a decline in GDP in most Western countries leading to the most pronounced recession since the Great Depression (Friedman 2010, 17; Hall 2010; Stiglitz 2010a, 6; Arestis et al. 2011, 1; Grusky et al. 2011; Tridico 2012; Redbird and Grusky 2016). In what follows, a particular focus will be placed on employment outcomes, notably the increase in unemployment rates, and the decrease and slow recovery of employment rates.

2.2.1 The Labour Market

The crisis led to a decline in availability of credit not only to individuals (Mian and Sufi 2010, 77), but also to banks and businesses (Stiglitz 2010a, 109; Chodorow-Reich 2014). The drying up of the credit market in particular had an effect on smaller companies. Chodorow-Reich (2014) finds that it was principally firms with fewer than 1,000 employees that made up the bulk of losses in employment. Moreover, this is further compounded by the fact that smaller firms rely far more on bank credit rather than other more long-term and possibly more stable forms of finance. Hall (2010) shows that, in the US at least, the majority of GDP decline can be explained by a substantial reduction in investment, be it in durable consumer goods, business, or housing. Therefore, industries requiring substantial access to bank loans either to operate or to spur consumption were far more affected by the crisis than the rest of the economy. Moreover, job losses further diminish investment which in turn can provoke further job losses as companies that rely on long-term investments have to turn to lay-offs. This was especially the case for the US auto industry, more particularly GM and Chrysler which saw huge losses in employment in order to receive government bailout plans (Goolsbee and Krueger 2015).

However, the substantial increase in unemployment wasn't only limited to manufacturing in the US (Goolsbee and Krueger 2015, 11). The crisis led to a decline in employment in almost all sectors. Job losses were, initially, more a consequence of firms going out of business than surviving firms laying off workers. This meant that "[v]ulnerable workers and privileged ones alike [had] to find new work." (Hout et al. 2011, 60), but this was no longer the case as the recession wore on and firms eventually had to fire more workers. Individuals with lower levels of education, of African-American descent as well as immigrants, and younger workers were more sharply affected by these lay-offs than other sociodemographic groups. More interestingly, in the US, the crisis affected men more than women (Pissarides 2013) as the employment rate for prime-age workers (25–54) declined more sharply for men. This is, in part, related to the industries that were most strongly affected by the crisis: construction and manufacturing and to a lesser degree finance (Hout et al. 2011, 78).

These trends in changes in employment and unemployment were not confined only to the US. Similar changes could be observed in most countries in the Organisation for Economic Co-operation and Development (OECD). The unemployment rate increased for most countries following the crisis (Keeley and Love 2010; Bernal-Verdugo et al. 2013; Pissarides 2013; Tridico 2013), but not all as in Germany and Poland the unemployment rate *declined* between 2007 and 2009. In Europe, the increase in unemployment was even more marked than in the US in certain countries, particularly in Spain and Ireland who not only had to deal with contagion from the financial crisis in the US, but also with the bursting of their own housing bubbles (Keeley and Love 2010, 52; Pissarides 2013).

Europe in particular saw notable increases in the youth unemployment rate especially in Southern Europe and its increase was more pronounced than in previous economic downturns (Arpaia and Curci 2010, 12; O'Higgins 2012). The greater increase in youth unemployment is especially salient as experiencing unemployment early in one's labour-market trajectory can have long-term consequences or scarring. Choudhry et al. (2012) looking at longer-term trends find that while the youth unemployment rate was steady and had even begun to somewhat decline before the crisis, it subsequently hit its highest level in a decade during the Great Recession in 2009. While they find that crises in general disproportionately affect younger workers, they find no evidence that the 2008 Financial Crisis was any different from previous crises in its effects on youth unemployment.

O'Higgins (2012) also investigates the impact of the crisis on youth unemployment and employment, and finds evidence that one of the potential factors behind the increase in youth unemployment is related to the low level of employment protection for temporary contracts especially relative to permanent positions. Countries with apprenticeship systems also saw less pronounced increases in youth unemployment during the crisis. These dual-education systems serve to smooth the transition between education and employment as well as better protect younger workers from the negative effects of a crisis on employment security (O'Higgins 2012, 405).

Furthermore, there is evidence that the Great Recession increased the likelihood of young individuals being NEET (Not in Education, Employment, or Training) (Dietrich 2013; Bruno et al. 2014). The crisis beyond just increasing the youth unemployment rate, and the proportion of NEET individuals, also increased the *persistence* of these states. In other words, the crisis also reduced the chances of younger workers and individuals to enter employment and prolonged their spells of labour market exclusion. More worryingly, Bruno et al. (2014) find that the NEET rate and the youth unemployment rate are not particularly sensitive to changes in the GDP suggesting that even as the economy recovers, youth unemployment may not decline very much.

Another issue particularly affecting younger individuals in the labour market is that the crisis led to an increase in the chances of being in unstable or temporary employment. A disproportionate number of jobs in Europe that were created after the crisis were temporary and these positions are overwhelmingly occupied by younger workers even outside of times of crisis (Choudhry et al. 2012). Nevertheless, Dietrich (2013) finds no evidence that the share of youth temporary employment in a country is associated with a higher level of youth unemployment overall over a ten-year period including the crisis.

However, prolonged labour market exclusion as a result of the crisis is not limited to the youth. Long-term unemployment rates in general increased during the Great Recession quite substantially. In the US, the average amount of time an individual was out of work in previous recessions was somewhere around nine weeks, but during the Great Recession, the average unemployment duration was 21 weeks (Hout et al. 2011, 69). In Europe, changes in the long-term unemployment rate – the percentage of unemployed without work for 12 months or more – were more heterogeneous (Heidenreich 2015). In some countries (most notably Spain and Greece but also the Nordic countries), the long-term, or persistent, unemployment rate almost doubled at the peak of the recession compared to pre-recession levels.

Pissarides (2013) further attempts to approximate to which degree the rise in unemployment in OECD countries between 2007 and 2009 is attributable to an increase in the number of individuals entering unemployment – that is a rise in short-term unemployment – and to an increase in the duration of individuals' unemployment spells. In most OECD countries, the rise in unemployment is principally due to individuals entering unemployment, but in the case of the US or Canada the contribution of the long-term unemployed was more substantial.

2.2.2 Austerity & the Sovereign Debt Crisis

When interbank lending and credit dried up following the 2008 Financial Crisis, countries whose economies relied on short-term lending were more severely affected. However, the signs pointed to most European countries being able to deal with a banking crisis, in particular Spain and Ireland, as their public debt ratios were not excessive. The starting point, however, was that these same countries in late 2009 projected a greater increase in public debt as fiscal revenues fell at a higher rate than GDP. The situation in Greece was even more dire as the deficit forecast was doubled and the deficit for previous years was revised upwards (Lane 2012).

Part of the problem was that while all government debt in the Eurozone is denominated in the same currency, government bonds did not have the same yields and countries perceived as being economically at risk saw their yields rise sharply relative to more stable countries such as France and Germany. Greece plunged further into crisis in 2010, when its bonds' rating was downgraded putting the country at risk of defaulting due to especially high government bond interests (Armingeon and Baccaro 2012; Lane 2012). Ireland and Portugal followed suit. This led to a joint EU and IMF bailout which provided a loan over a period of three years on the condition of the recipients implementing fiscal austerity and structural reforms. This was further compounded by a break in private-sector lending to European banks due to the perceived risk of European banks' holdings.

Another more general issue that affected almost all countries was that governments used a substantial amount of the public budget to bail-out the very financial institutions that instigated the crisis in the first place in order to prevent a potential systemic collapse of the financial system – the "too big to fail" narrative. After using public finances to save private institutions, most countries then proceeded to cut public spending in order to reduce their debt in order to show markets that they were willing to do anything to guarantee the stability of the financial sector (Blyth 2013, 3–4). Moreover, austerity, which was supposed to send a reassuring signal to markets after public debt rose as a consequence of those same private institutions causing a crisis and a recession, instead made banks riskier as the government bonds they held saw their interest rates increase.

Even if the bailout packages, the reforms, and austerity were supposed to solve the debt crisis in these countries and put them back on the path to economic recovery, there is more evidence that these measures did more harm than good and contributed to prolonging the recession in countries which received the bailout. In fact, austerity in general, contrary to beliefs that it can serve to increase economic growth in the short term, has contractionary effects on economic growth (Guajardo et al. 2014). After beginning the implementation of austerity measures and structural reforms, economic growth in Europe didn't recover and in fact these programmes have not had beneficial effects (Stiglitz 2014, 64–65). Stiglitz (2014) in fact argues that European leaders' choice to impose austerity only made things worse and that austerity is only effective in smaller economies that can compensate by increasing exports to trade partners in better economic standing. House et al. (2019) who define austerity as a lower than expected level of government purchases, further find that austerity almost entirely explains the drop in economic growth for European countries after 2010, especially in the case of Greece, Ireland, Italy, Portugal, and Spain (GIIPS).

Moreover, austerity not only affected public finances, but also required further economic adjustments as alternatives to other economic policy changes that are normally available during economic crises. The countries who adopted the Euro as their domestic currency have more or less no direct manner in which to devalue it without having to resort to measures which put employees at a disadvantage such as internal devaluation i.e. exerting a downward pressure on national prices and wages. However this isn't a particularly viable solution in the long term (Armingeon and Baccaro 2012) and can serve to further prolong recession as it also decreases demand and consumption. This is further explored by Stockhammer and Sotiropoulos (2014) who find that the cost in terms of GDP to balance current account deficit would be substantial. Instead, they argue that rather than adjusting downwards through deflationary policies in the GIIPS group of countries, a less destructive option would have been for countries with current-account surpluses to engage in inflationary measures.

2.2.3 Inequality & Poverty

Income

While one of the attributed causes of the 2008 Financial Crisis in the US is growing income and wealth inequality (see Section 2.1), the crisis has only further exacerbated inequality. In the case of the US, Smeeding et al. (2011) shows that income inequality grew over time and further increases after periods of economic crisis. In fact, only the top two income quintiles saw their share of income stay stable or increase. Furthermore, growing income inequality seems to be predominantly due to the rising income share of top earners in general. However, there is evidence that the increase in income inequality in the Great Recession is due to a sharp decline in the income share of the lowest quintile – principally in relation to the rise of the unemployment rate. Burkhauser and Larrimore (2014) further compare the decline in median income in the US during the Great Recession to previous recessions. They find that prior the Great Recession, median income in the US hadn't recovered to the same level as before the last recession in 2001.

In terms of the change in the level of inequality over time, the Great Recession saw substantial year-on-year increases, but the increase was not as substantial as it was during the 1980s. A further decomposition in the growth of inequality over time by Burkhauser and Larrimore (2014) shows that inequality remained relatively stable in the top income bracket (top 5%), but increased substantially among lower-income groups further illustrating that increases in inequality are related to a drop in wages for the poorest members of the US population. This is compounded by the fact that the Great Recession mainly led to a decrease in income not through wage decreases for those who were employed, but through a substantial increase in the number of unemployed. Additionally, compared to previous recessions, the Great Recession had a greater increase in part-time unemployment which also leads to a decrease in the median wage despite the increase in the wages for full-time employment (Burkhauser and Larrimore 2014, 119–120).

However, other measures show that inequality related to household-level incomes in the US didn't necessarily increase over time in the short term – 2007–2009 (Jenkins et al. 2012; Thompson and Smeeding 2012). In fact, compared to previous downturns, the increase in income inequality was far less pronounced than the increases that occurred in previous recessions. Thompson and Smeeding (2012) tempers this finding as once elderly households, households headed by a person aged 65 or older, are excluded a trend of increasing inequality appears. This can in part be explained by the elderly relying on sources of income not derived from employment which were less affected by the crisis and US social transfer programmes generally targeting the elderly more than younger individuals.

In broad comparative analysis, Jenkins et al. (2012) compare data on income inequality using the EU Statistics on Income and Living Conditions (EU-SILC) survey. They find, in Europe, that net median household income in fact increased in the early period of the Great Recession (2007 to 2009) and only really decreased in Spain and the UK. Moreover, looking at different measures for income inequality – Gini coefficient and the 80/20 percentile ratio – the data show that in most countries there was a *decrease* in inequality except in Spain and in Denmark, where there were non-negligible increases. Consequently while growing inequality may have been a cause of the crisis, it would seem that, in Europe especially, the Great Recession didn't contribute to further increases in income inequality.

Wealth

In terms of wealth, the Great Recession led to a greater decline in median wealth than previous recessions partially as consequence of the collapse of the housing market, and the high leverage of many households. Wolff (2014) looks at the evolution of wealth and wealth inequality in the longer term in the US using the Federal Reserve's Study of Consumer Finance (SCF). After a sharp increase during the 1980s, wealth inequality remained relatively stable until just prior to the Great Recession. This increase was principally spurred by the rise in importance of the stock market and its contribution to household wealth. The rise in wealth after the crisis didn't occur within the top one percent of the distribution but rather in the top five percent of the distribution. However, the rise in inequality is mainly due to a sharp decline in wealth in the lower quantiles of the wealth distribution and the relative increase of households with no or negative net worth.

Wealth inequality was further increased in the aftermath of the Great Recession as the savings of the wealthiest didn't depend nearly as much on property ownership. The top one percent of households by wealth according to the SCF only invested nine percent of their wealth in housing while the next 19 percent of wealthiest households had a much more substantial amount of wealth in housing (around 30 percent). Households with less wealth had far more money invested in housing, personal savings, and pension accounts. Moreover, less wealthy households had far more debt meaning their net wealth was substantially reduced relative to their assets. Moreover, housing prices dropped more proportionally than the stock market further contributing to an increase in wealth inequality as less wealthy households had far more invested in housing than in other assets.

Pfeffer et al. (2013) also investigate changes in wealth using the Panel Study of Income Dynamics and household-level repeated measures. This allowed them to look at relative changes in wealth over time for households. When comparing total net worth in 2011 to 2003, the top quartile saw almost no reduction even if they lost wealth after an increase until 2007. The bottom quartile saw their relative wealth constantly decrease since 2003 and median wealth had decreased by nearly 50 percent in 2011 relative to 2003. The differences in the decline of relative wealth are further accentuated when excluding housing and real estate wealth as the top quartile gained wealth despite the recession while the bottom three quartiles all saw their non-housing and non-real-estate wealth decrease.

The differences are even more stark when looking at inequality indicators such as the Gini coefficient or percentile ratios with the 95/25 ratio increasing nearly sevenfold between 2003 and 2011. More notably, the 50/25 ratio also increased substantially further illustrating that the Great Recession disproportionately affected households at the lower end of the wealth distribution. Furthermore, quintile mobility rates show that a not insubstantial proportion of households experienced a downward transition in their position in the wealth distribution within the third and fourth quintiles, while households in the top quintile overwhelmingly remained there. In fact, the recession accentuated the chances of households in the middle of the wealth distribution moving downwards. As for the lowest-income households, the vast majority remained in the lowest quintile.

There is comparatively less research on changes in wealth inequality in Europe in the aftermath of the 2008 Financial Crisis. Grabka (2015) looks at the case of wealth inequalities in Germany during the Great Recession. Using data from the German Socio Economic Panel, standard inequality measures suggest that there wasn't any increase of note in the level of wealth inequality in Germany after the crisis. On the basis of the 90/50 percentile ratio and the 75/50 ratio, it would seem that inequality slightly decreased mainly due to a shrinking of wealth for the top of the distribution. However, it would in part appear that this is due to wealth losses being principally limited to the short-term and Germany's relatively quick recovery from the Great Recession.

A summary of the evolution of wealth inequalities in OECD countries by Bogliacino and Maestri (2016) in the aftermath of the Great Recession suggests that in the slightly longer term, wealth inequality *did* increase between 2010 and 2015. They find that while financial assets did lose value initially after the crisis, their prices recovered much more quickly than did property prices (as is also noted by Wolff (2014)) and as it is often wealthier households that hold these types of assets, this would contribute to an increase in wealth inequality once countries began to recover from the recession. Similarly, Balestra and Tonkin (2018) find that in the large majority of OECD countries, wealth disparities further increased following the crisis but in addition find that, in the case of the UK, Italy, and Australia, decreases in wealth disproportionately affected younger households when compared to households headed by individuals over the age of 65. As for changes in distribution, overall there is a tendency towards an increase in wealth inequality as measured by the mean–median ratio for certain countries such as the US, the UK, Spain, or Greece but a decline in others like Germany, Austria. Further investigation of the share of net wealth held by the top ten percent of households again shows a very slight decrease overall in the OECD and more marked increases in the US, the UK, Spain, and Greece with smaller increases in France, Norway, or Finland. Again, Germany and Austria saw declines and so did Italy, and Belgium. Consequently, it would seem that the Great Recession generally didn't lead to major changes in the distribution of wealth in most Western countries but did lead to increases most notably in the US and the UK.

Poverty

As in the case of income and wealth inequality, there is no clear pattern of change in the case of poverty during the Great Recession. Smeeding et al. (2011) and Thompson and Smeeding (2012) find that just as in previous recessions, the Great Recession led to a rise in the officially defined poverty rate (defined according to prices in a given year; an absolute measure) in the US, though early on it had yet to reach the heights of recessions in the ’80s or ’90s. The overall poverty rate increased to nearly 15 percent in 2009 and the rise in poverty disproportionately affected younger households as well as households experiencing unemployment or with earners in part-time employment. However, the poverty rate among older households dropped to its lowest level in 50 years. Using another poverty measure which includes social transfers among sources of income and takes into account consumption patterns, Smeeding et al. (2011) find that the poverty rate increased more dramatically during the recession than the official rate. In the medium-term, the official poverty rate had declined by 2013, but it was still above the level prior to the Great Recession (Redbird and Grusky 2016). Overall, in the US the Great Recession did lead to rise in poverty as in the case of previous recessions, and it more strongly affected younger individuals though child poverty rates didn’t seem to fundamentally change during the recession (Wimer and Smeeding 2017).

Jenkins et al. (2012) find that when taking either absolute or relative measures of poverty, there is more or less no change in relation to the Great Recession in Europe. In fact, across 15 European countries, only Spain, the UK, and Denmark experienced a very slight increase in the *absolute* poverty rate (at most a two percent increase) while there was a very modest increase in the *relative* poverty rate in Denmark, France, Germany, Spain, and Sweden (at most an increase of 1.5 percent). Overall, the Great Recession didn’t signal a departure from previous trends in the evolution of poverty rates in Europe. However, this is a short-term picture as it mainly concerns a two-year period after the crisis where unemployment benefits would have better been able to provide additional income support.

In the medium term, overall poverty – relative and anchored/absolute – in certain countries such as Belgium (Vinck et al. 2017), Germany (Bahle and Krause 2017), or the UK (Bourquin et al. 2019) remained more or less flat or only saw modest increases after the crisis followed by a quick return to pre-crisis levels. Countries more strongly affected by the crisis such as Spain, Ireland, Italy, or Greece on the other hand didn’t necessarily see relative poverty increase. In the case of Ireland relative poverty decreased over time, but this is due to a substantial decrease in the median income during the recession. Using an anchored poverty measure shows a drastic increase in poverty after the recession in Ireland (Nolan and Maître 2017). It is a similar situation for Spain with relative poverty being rather stable (though slightly increasing in 2014) and a substantial increase in anchored poverty (Ayllón 2017).

Hick (2016), using a multidimensional approach with EU-SILC data, compares poverty in 2013 and 2005 and also finds modest increases as in the case of France, Sweden, the Netherlands, Italy, or Denmark but also decreases in countries such as Germany, the UK, or Poland, with more pronounced increases in Spain, Greece, or Ireland. Hick further decomposes change over time by looking at the change in multidimensional poverty between 2005 and 2008, 2008 and 2011, and 2011 and 2013. Even in countries which saw an overall decline between 2005 and 2013 such as the UK or Germany, there was an increase in multidimensional poverty between 2008 and 2011 which was undone later on between 2011 and 2013. In the case of Greece, most of the overall increase is driven by substantial increases between 2008 and 2011, and between 2011 and 2013 while in Spain, the increase in poverty is mostly due to a large rise in the 2011–2013 period. For France, Italy, the Netherlands, and Denmark, the increases in poverty were more pronounced in 2008–2011 than later on. This suggests that while patterns of poverty increases in Europe were relatively similar immediately in the wake of the 2008 Financial Crisis, the divergences principally occurred in the medium-term.

2.2.4 Health

A substantial line of enquiry in the aftermath of the 2008 Financial Crisis, also related to austerity and the sovereign debt crisis in Europe, is the investigation of health outcomes. Studies investigate whether health was directly affected due to the stress of the crisis, but also the extent to which the reduction of social spending in relation to austerity had the negative consequences for nationalized healthcare systems. In many cases, healthcare was among the first domains to see cuts after the implementation of austerity measures (McDaid et al. 2013; Borisch 2014; Reeves et al. 2014; Gool and Pearson 2014; Basu et al. 2017). In fact health spending didn't only decline in countries that had to implement austerity measures but also in countries such as Denmark or the United Kingdom (Morgan and Astolfi 2014) which weren't subject to the Troika's imposition of austerity.

A large cross-national comparison by Karanikolos et al. (2013) compares changes in health outcomes during the Great Recession to those in previous economic downturns. Evidence from previous recessions is conflicting and this is further compounded when comparing studies using aggregate data to those using individual-level data. At the aggregate level, there is evidence that economic crises can have a *beneficial* effect on health even if at the individual level, there can be substantial negative effects on health. This is in part attributed to attitudinal changes most notably a decline in road traffic (Baumbach and Gulis 2014). In the case of the current financial crisis, there is evidence that, in European countries hardest hit by the crisis, there was an increase in the prevalence of mental health issues (Greece and Spain), a decline in self-reported health and access (Greece), and a general increase in the number of suicides across the entire EU, especially among the EU-15 countries.

In the UK in particular, there is evidence that the rise in suicides in England is related to the rise in unemployment experienced during the same period (Barr et al. 2012). In Greece more specifically, Kentikelenis et al. (2014) report that the incidence of mental health issues increased substantially between 2008 and 2011 and the main risk factor associated with this rise was economic hardship. The incidence of suicides and suicide attempts also increased compared to 2007 and the differences between men and women declined over time. The effects of the crisis are less clear for Spain according to Regidor et al. (2014). They find, at the macro level, that the declining trend in premature mortality continued during the crisis at rates similar to prior periods except for HIV- and cancer-related mortality which stagnated. However, Lopez Bernal et al. (2013) find that the suicide rate increased at a greater rate than previously with the onset of the crisis indicating a decrease in overall mental health in Spain. Baumbach and Gulis (2014) find that the suicide rate increased even in countries that were less affected by the crisis such as Germany and Poland. They also find that there is evidence that the relationship between unemployment and suicide is likely to be stronger in countries where social spending is lower as these countries have fewer resources with which to help individuals.

A study among older workers (50–64) by Riumallo-Herl et al. (2014) comparing Europe and the United States finds that becoming unemployed led to an increase in depression, though the increase was more pronounced in the US. Moreover, there was no change or even a decrease in the level of depression for individuals who remained employed. The increase was even more pronounced among individuals who lost their jobs through plant closures or their employer going out of business. Another difference between Europe and the US in relation to job loss and depression was the role of wealth. In the US, job loss led to a more pronounced increase in depression for less wealthy individuals further suggesting that the crisis more strongly affected the mental health of more economically vulnerable individuals than in Europe.

Drydakis (2015) looks at the link between unemployment, and mental and self-rated health using individual-level longitudinal data. He finds, for both men and women, that unemployment led to a decrease in self-rated health and mental health. Like Riumallo-Herl et al. (2014), Drydakis also finds that unemployment caused by firm closure has an additional negative effect on health beyond simply experiencing unemployment.

Beyond just a direct impact on individual health, austerity and the recession have also affected the access to and the financing of healthcare systems which also contributes to a decline in individuals' health. In Greece, the government simultaneously cut health expenditure *and* increased out-of-pocket costs associated with using health services (Stuckler et al. 2017). In Greece in particular, cuts to health-related spending were severe in order to meet the requirements set out by the Troika. Kentikelenis et al. (2014) find that the cuts particularly affected more vulnerable individuals. For example, the HIV infection rate among drug users substantially increased between 2008 and 2012, the incidence of tuberculosis increased, and malaria even made a return. Moreover, end-user costs increased especially for consultations and prescriptions.

More troubling is that access to healthcare is dependent on employment, and with growing long-term unemployment, the proportion of individuals with no healthcare coverage increased substantially. Furthermore, the likelihood of individuals having unmet medical needs also increased, with the inability to afford medical treatment increasingly becoming a reason for having unmet needs. In Portugal, Legido-Quigley et al. (2016) also find that incidence of unmet healthcare needs substantially increased in the aftermath of the crisis especially among employed individuals.

Moreover, the incidence of individuals having unmet medical needs because they couldn't afford to pay for healthcare also rose.

The consequences of the crisis on health were wide-ranging and important. Though the situation degraded the most in the case of countries which were forced into implementing austerity and severely reducing government spending – Greece, Spain, Portugal, Italy, or Ireland – the crisis nevertheless led to negative consequences for health in almost all countries including those hadn't cut public spending for healthcare.

2.3 Conclusion

This chapter provided an overview of the origins and consequences of the 2008 Financial Crisis and the subsequent Great Recession. There are a multitude of lines of enquiry into the explanation of the crisis – in fact it might be over-explained or over-determined in relation to the myriad causes and explanations offered for the crisis (Lo 2012; Blyth 2013, 22). What is clear is that the crisis was set off by a decrease in housing prices in the US.

The causes of the US housing bubble are more contentious. On the one hand, some blame the government for encouraging and facilitating home ownership. They contend that government policies allowed for households without the necessary financial resources to buy housing they couldn't afford. On the other, critics argue that sub-prime mortgages, which are considered to have made financial instruments less secure, were not given to households who would have been eligible to receive loans from the federally backed Fannie Mae and Freddie Mac in the first place.

Another aspect is the development of the shadow banking sector and the financial derivatives market. Initially seen as a safer way to invest in less secure assets, its expansion was driven by substantially higher returns compared to more standard financial products. A shift from an originate-and-hold model of providing to loans to an originate-and-distribute model further contributed the risky nature of financial derivatives. This manner of functioning meant that the institution that initially provided the loan to the borrower actually sold it on to investors. This incited lenders to be more lax in their checks and requirements, and in certain cases even incited them to encourage households to take out mortgages to take advantage of rising housing prices.

The shadow banking sector was also characterized by another factor that contributed to its proliferation: an absence of regulation (Krugman 2008). Any effort to impose regulations on the shadow banking system was combated and banks increasingly used it as a way to skirt capital requirement regulations and move to riskier but more profitable investments. The lack of regulation of this sector also meant a lack of regulation in the rating of financial derivatives. Rating agencies are supposed to provide an indication of the risk associated with financial derivatives, but they are also paid by financial institutions to do so. This incites rating agencies to provide more favourable ratings to financial derivatives relative to their actual level of security.

Nevertheless, this doesn't explain how a crisis that originated in the US, and was almost entirely caused by events specific to the US, spread so far and so quickly. One explanation provided by Pernell-Gallagher (2015) is that the higher returns on financial derivatives incited banks, particularly those in Europe, to invest in these financial products in an effort to match the performance of US-based banks. A more contentious explanation is that there was an abundance of savings – a "global savings glut" – especially in South-East Asia which provided American banks with a large quantity of capital to invest.

A more long-term view contends that the housing bubble in itself is just a consequence of growing income and wealth inequality since the 1980s. In the US especially, this led to a growing number of households seeing their wages stagnate while the cost of living continued to climb. This led to the development of debt-driven growth where households had to take on debt in order to keep up a certain standard of living corresponding to their social position. The differences are even more flagrant in the case of wealth which became increasingly concentrated in the upper percentiles of the distribution in almost all Western countries (Piketty and Saez 2014). As such, the 2008 Financial Crisis was set off by declines in the US housing market, but in reality it was one event in a series of cumulative problems related to wealth and income accumulation that have been going on since the 1980s in particular.

The causes of the crisis, be it in a short- or long-term perspective, are relatively well understood but the consequences, especially in the long-term, are less clear. In the short-term, the 2008 Financial Crisis led to a marked decline in the GDP of most Western Countries and the biggest recession since the Great Depression. Unemployment rates increased substantially in many countries. In the US the unemployment rate nearly doubled and the industries that most benefited from the construction boom, construction and manufacturing, saw the biggest decline in employment. As a consequence, this crisis led to a more pronounced increase in unemployment levels for men than for women overall. In the European countries subject to the Troika-imposed austerity measures – Greece, Spain, Portugal in particular – youth unemployment increased substantially (O'Reilly et al. 2015). The recovery from the crisis especially in terms of the labour market was slower than previous crises (Redbird and Grusky 2016). The OECD for instance considers that it is only in 2018 that employment levels had returned to near pre-crisis levels (OECD 2018, 11).

Inequality itself has also progressed in the aftermath of the crisis. While in the period immediately following the crisis there is some evidence to suggest a slight decline in inequality, in the medium term, income and wealth inequality continued to rise. In the US, the increase in income inequality during the Great Recession was mainly driven by a decline in the share of income held by the bottom of the distribution while top incomes stagnated. However, the share of the income held by the top earners, has returned or is returning to pre-crisis levels but is declining for the bottom of the distribution in Anglo-Saxon countries (Alvaredo et al. 2017, 54). By contrast, in Europe the crisis didn't have much of an impact on income inequality and in most cases it hasn't grown since the crisis (Alvaredo et al. 2017, 72–73).

The increase in wealth inequality was even more pronounced, especially in the

US, as most households outside of the top of the distribution derive most of their wealth from their housing ownership. The collapse of the US housing market, and the substantial amount of household debt related to mortgages, led to a decrease in wealth especially outside the top 10% of the distribution. Once again in Europe, the crisis didn't affect the distribution of wealth nearly as much as in the US and in many cases the Great Recession did little to alter preexisting trends in wealth inequality.

Where the crisis did have a more obvious impact, especially in Europe, is on poverty and health outcomes. In the countries most affected by austerity measures (Greece, Spain, Portugal, Ireland, and Italy), poverty when not measured using relative thresholds also increased substantially when compared to the situation prior to the crisis, as well as in comparison to countries who weren't subject to austerity. Moreover, while many countries saw their poverty rates decline in the longer term after the crisis, this was not the case for the GIIPS countries for which poverty with poverty increasing after 2012.

As for health, there is evidence that the substantial increase in unemployment led to a greater incidence of mental health problems. Moreover, the increase was more pronounced among the countries hardest hit by the crisis such as the GIIPS group. There is also evidence, in the case of both Europe and the US, that unemployment due to a firm closure had a greater effect on mental well-being than just becoming unemployed.

Beyond mental health, self-rated health also declined due to the massive increase in unemployment. In the GIIPS countries where health spending declined with the introduction of austerity measures, the proportion of individuals with unmet medical needs due to financial difficulties increased. The incidence of HIV infections among drug users did as well, and certain diseases such as malaria even made a return.

While the focus of this chapter was on the origins of the crisis and the consequences mainly at the individual level, the crisis also had broader ramifications. The spread of austerity and the accompanying welfare state retrenchment not only affected countries under the EU–ECB–IMF Troika, but almost all European countries (Taylor-Gooby et al. 2017).

In the political domain, austerity measure saw the rise of left-wing populist parties in both Greece, with Syriza, and Spain, with Podemos, which resulted in an increasing political polarization (Mudde 2016). In the UK, the rise of the Scottish National Party and Plaid Cymru in Wales is also attributed to taking an anti-austerity line in the face of more pro-austerity mainstream parties (Massetti 2018). Fetzer (2019) even argues that austerity may have been a contributing factor to Brexit. In Italy, both the Northern League (*Lega del Nord*) and the Five Star Movement (*Movimento 5 Stelle*) positioned themselves as anti-austerity parties (Ivaldi et al. 2017) and subsequently won the most seats in the 2018 Italian general election (D'Alimonte 2019).

To conclude, the 2008 Financial Crisis and the ensuing Great Recession have had wide-ranging effects in many domains of life. As two of the defining events of the 21st century, it is likely that the consequences will be felt for many years in the future. Even now, the medium-term consequences of the crisis are still being explored. The policies and governmental decisions that facilitated the occurrence of the crisis and the recession haven't been revised. Instead, the tendency was for governments to maintain the status quo and for the very financial institutions at the centre of the crisis to lobby against any regulations that would force them to change their manner of operating (Helleiner 2014). As a result, the occurrence of similar crises in the future cannot be excluded. Moreover, there is a chance that the consequences of a future crisis would be potentially more devastating in light of the welfare retrenchment that has occurred under the auspices of austerity and the relatively weak recovery.

Thus, the 2008 Financial Crisis is a major sociohistorical event which challenged, and continues to challenge, people's lives and livelihood as well as their position on the labour market. In a certain manner, the crisis represents a catalyst that in some individuals revealed their vulnerability while for others it revealed their lack of vulnerability or their resilience to the (economic) stress caused by the crisis. The crisis therefore offers the possibility to investigate differences in individual vulnerability. In other words, the crisis exposed differences in the individual chances of experiencing the myriad negative consequences associated with this event in domains such as health, well-being, poverty, or labour market outcomes. It is this last domain on which this thesis focuses and which will guide the analysis of vulnerability concepts, and the development of framework for analysis that will be presented in Chapter 3.

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Chapter 3 Defining Vulnerability

Vulnerability, as a concept, can be broadly defined as the likelihood of experiencing negative consequences in relation to exposure to a source of stress or an unexpected event. Thus, most approaches to conceptualizing vulnerability refer at least to two components: (1) a source of stress which can in turn lead to (2) a worsening of circumstances. As the concept of vulnerability is used in many domains, the negative consequences and events/stressors examined depend on the discipline.

In the environmental sciences – more specifically disaster studies – the focus is often at a level higher than the individual level, such as the household or community, and looks at, for example, outcomes that can vary from economic recovery and rebuilding after a natural disaster, to preserving agricultural livelihood. Another topic that often appears is vulnerability to the consequences of climate change and their destructive potential for individuals' and households' livelihoods. In this domain, the conception of vulnerability has evolved from a view almost exclusively centred on the occurrence of destructive natural phenomena to one incorporating socially produced vulnerability (Blaikie et al. 1994; Cutter 1996; Bankoff 2001; Cutter et al. 2003; Turner II et al. 2003; Kasperson et al. 2005; Füssel 2007).

In the social sciences, the negative consequences that are most often investigated are poverty, and social exclusion (Chambers 1989; Beck 1992; Castel 1995; Esping-Andersen 2002; Taylor-Gooby 2004; Whelan and Maître 2005; Paugam 2007, 2009; Ranci 2010; Standing 2011; Spini et al. 2013; Whelan and Maître 2014; Hanappi et al. 2015; Spini et al. 2017) A central concern in this literature is the multidimensionality of vulnerability or precariousness, and the role of the welfare state in reducing vulnerability, or at least attenuating it.

In psychology, much of the focus is on depression or well-being (Pearlin et al. 1981; Kessler and McLeod 1984; Pearlin 1989; Aneshensel 1992; Ingram et al. 1998; Spini et al. 2013; Hanappi et al. 2015; Spini et al. 2017). In these "stress" models, the main interest is *social vulnerability* or psychological distress caused by events that occur in the social sphere. One of the main themes within this literature is explaining differences in outcomes when individuals are exposed to sources of stress, and trajectories of recovery. Another direction of enquiry is the contribution of differences in the risk of exposure to sources of stress to differences in the observed outcomes.

In this chapter, I will first summarize different approaches and views of vulnerability as well as the closely related concepts of risk and resilience. I will further clarify how these different concepts can be distinguished and integrated. Finally, I will outline how I intend to link a dynamic view of vulnerability heavily derived from the framework presented by Spini et al. (2013) and Spini et al. (2017) to an analysis of vulnerability in relation to labour market outcomes in the aftermath of the 2008 Financial Crisis which is considered as the stressor. This will be further developed in the two applications in Chapters 6 and 7.

3.1 Retracing the Concept of Vulnerability

The concept of vulnerability is employed in a multitude of disciplines, and consequently is not always clearly defined nor employed in a consistent manner even within disciplines (Levine et al. 2004; O'Brien et al. 2004; Füssel 2007; Misztal 2011; Spini et al. 2013; Oris et al. 2016; Spini et al. 2017). Some consider that the term and concept itself entered the social sciences through the field of disaster studies or hazards research (Füssel 2007; Misztal 2011) and has subsequently grown in popularity and use in the social sciences. However, while this may have contributed to the expansion of the use of vulnerability in the social sciences, there are nevertheless similar concepts such as precariousness or precarity, social exclusion, or risk that have been employed in the social sciences and which have substantial overlap with vulnerability (Beck 1992; Castel 1995; Taylor-Gooby 2004; Paugam 2007, 2009). Moreover, there is also the use of the concept of vulnerability in relation to social stress and psychological distress which itself dates back to the 1970s and is illustrated by work such as the stress process model of Pearlin (Pearlin et al. 1981; Pearlin 1989, 2010) and other work on social stress (Kessler 1979; Turner and Noh 1983; Kessler and McLeod 1984; Kessler et al. 1985; Aneshensel 1992; Kessler 1997). In this section we will retrace the development of different definitions of vulnerability principally in the environmental and social sciences. There will be less of a focus on social stress models as we will come back to them when discussing the dynamic framework for modelling vulnerability in Section 3.3.

3.1.1 Disaster Studies & the Environmental Sciences

Initially, vulnerability in the environmental sciences, and more particularly in the domain of disaster studies, took a relatively passive view of vulnerability and considered it as mainly a "technical" problem. As such, the interest was not on how natural hazards would affect individuals and how they would cope with them, but rather on preventing them from having any consequences through the mitigation of risks and better preparedness in dealing with natural disasters. This view is most often called the "risk-hazard" or "exposure model" (Bankoff 2001; Cutter et al. 2003; Turner II et al. 2003; Füssel 2007) which posits that the impact of a hazard depends on the "sensitivity" of the exposed subject. Vulnerability is not an essential part of this model, and the model itself doesn't distinguish or seek to explain differences and variations in the consequences of hazards. This model essentially considers that different societies and different regions have different likelihoods of experiencing a hazard, but seems to ignore the social aspects of how societies can prepare themselves to respond to hazards, or socially produced vulnerability. In this framework, the focus is principally on biophysical aspects that make a geographic region more likely to experience damage. Therefore vulnerability, in a sense, is the difference between the severity of the hazard and its damage potential, and the damage done.

However, more recent approaches (Blaikie et al. 1994; Cutter 1996; Bankoff 2001; Cutter et al. 2003; Turner II et al. 2003; Kasperson et al. 2005; Füssel 2007) acknowledge the importance of social structures, the distribution of socioeconomic resources, and individual characteristics in explaining different outcomes after exposure to similar hazards. This approach in disaster studies, also called the "social vulnerability" approach, considers that disasters are not only a consequence of exposure to environmental risks, but also an uneven distribution of resources to deal with the risks to which people are exposed. This shift came as the fallout from natural disasters began to get considerably worse over time, yet there didn't seem to be an increase in the number of natural events occurring. This suggested that there was something beyond just preparing for the occurrence of "extreme natural phenomena".

In this view of social vulnerability, natural disasters have an external component related to the physical environment, but this is coupled with the inhabitants' resources and capacity to minimize changes in the physical environment and cope with them. However, this ability is socially stratified and the state often doesn't provide the same resources to everyone. Thus, when a society is faced with a natural event, or an external risk, the magnitude of the disaster is not only relative to any technical steps taken to mitigate the physical consequences, but is also linked to how individuals are able to deal with the expected changes in their environment after a specific natural phenomenon or external shock. Consequently, the focus of social vulnerability approaches (sometimes also called pressure-and-release models) is to determine what makes an individual – or a system, a household, etc. – more likely to experience harm or loss. The individual characteristics that are most commonly investigated, such as socioeconomic status, labour market status, education, age, gender, or ethnicity, are also studied in other disciplines and approaches to vulnerability as we will later see.

More recently, there has been somewhat of a convergence in the environmental sciences towards, if not a shared definition, a common framework for vulnerability. A minimal, shared definition of vulnerability that often emerges is that "[. . .] vulnerability to environmental hazards means the potential for loss", (Cutter et al. 2003, 242) or that it is "[. . .] the degree to which a system, subsystem, or system component is likely to experience harm due to exposure to a hazard, either a perturbation or stress/stressor." (Turner II et al. 2003; see also Bohle et al. 1994; Intergovernmental Panel on Climate Change 2001; Luers et al. 2003; O'Brien et al. 2004; Vatsa 2004; Kasperson et al. 2005, 250–253) However, within this common view of vulnerability there remain different conceptions and frameworks qualifying vulnerability.

In the framework proposed by Turner II et al. (2003), vulnerability has three interrelated components: exposure, sensitivity, and resilience. Exposure refers to the interaction between an external hazard and the systemic "components" that are affected, as well as the characteristics of the hazard itself. In a sense, for there to be vulnerability, or for it to manifest itself, there needs to be an element of exposure to a hazard. Exposure in this framework is a component in the determination of vulnerability. The second aspect is "sensitivity" which refers not only to social or "human conditions" – unlike the social vulnerability approaches – but also to the environmental conditions and the interaction between these two elements which Turner II et al. (2003) argue is neglected in the social vulnerability or pressure-and-release model. The final aspect of vulnerability is "resilience" which refers to recovering from the negative consequences of a hazard as well as any coping, adjustment, and adaptation mechanisms mobilized in response to the hazard.

Similarly, Cutter et al. (2003) considers that vulnerability is dependent on hazard potential, that is the chances of a natural hazard occurring, the geographic context or physical environment – biophysical vulnerability – and the social context – social vulnerability. The geographic context and the social context mutually influence each other and therefore indirectly the two forms of vulnerability are mutually dependent. These two aspects of vulnerability consequently define a specific place's vulnerability. However, where this framework differs somewhat from the risk-hazard model is that there is a feedback loop between vulnerability and hazard potential as vulnerability conditions the risk of a natural hazard, but also the mitigation strategies which in turn determine the hazard potential.

This is further summarized by Kasperson et al. (2005) who break down vulnerability into the same three aspects as Turner II et al. (2003): exposure, sensitivity, and resilience. As in the above frameworks, vulnerability requires being exposed to stressors. Once exposed to a stressor, vulnerability is subsequently determined by the ability to anticipate or cope with the stressor. Finally, the resilience component relates to the ability of an actor or unit to recover from the stress, but also to adapt and protect, or "buffer", itself against any future exposure to sources of stress.

A similar summary is proposed by Hufschmidt (2011). Hufschmidt considers that vulnerability encompasses the range of activities and possibilities of actors prior to, during, and after the occurrence of a hazard. Activities that occur prior to a hazard serve to limit the *potential* degree of damage which is considered to be a period of adaptation or anticipation. During the hazard, there is only reaction and activities focus on dealing with immediate damage or adverse effects. The final stage is recovering as well as the beginning of the adaptation phase in order to deal with long-term damage and to recover from the immediate damage of the hazard. Activities for each temporal period relative to exposure to a hazard can overlap and do not necessarily occur sequentially. For example, activities in the post-impact phase of a hazard can overlap with those in the pre-impact phase. Moreover, these activities are conditioned by the more general context, be it social, political, geographical, the build environment, available resources, etc.

To conclude this overview of the development and use of the concept of vulnerability in the environmental sciences, there seems to be a convergence in the definitions of the concept to one that is characterized by three aspects: exposure, coping/sensitivity, and recovery/resilience (Kasperson et al. 2005; Adger 2006). While there may be differences between frameworks concerning what elements are used to measure or operationalize sensitivity or the (physical or geographical) level at which vulnerability is assessed, the vast majority of modern approaches to vulnerability in the environmental sciences contain these three elements. Vulnerability, defined by these three elements, is considered to determine to varying degrees the potential for loss for an actor in relation to a hazard. There is also an increasing awareness within disaster studies of the necessity of embedding studies of vulnerability within the broader context, as well as the interplay between different levels and scales of the (social) environment. Vulnerability doesn't occur at a single level (Blaikie et al. 2003).

3.1.2 Social Sciences

Other concepts in the social sciences, such as precariousness, social exclusion, or risk, are very similar and it is possible to draw parallels between them and vulnerability as viewed in the environmental sciences. These concepts and their use were also contemporaneous with the development of the social vulnerability perspective in the environmental sciences. Because of the broader background of these concepts, there is less consistency between the different definitions and terms used in the social sciences in reference to vulnerability or closely connected concepts.

An early definition of vulnerability that has many commonalities with more current views of vulnerability in the environmental sciences is provided by Chambers (1989, 1) and is employed in order to distinguish the study of vulnerability from the study of poverty. For Chambers:

> "Vulnerability, though, is not the same as poverty. It means not lack or want, but defencelessness, insecurity, and exposure to risk, shocks and stress. [...] Vulnerability here refers to exposure to contingencies and stress, and difficulty in coping with them. Vulnerability has thus two sides: an external side of risk, shocks, and stress to which an individual or household is subject; and an internal side which is defencelessness, meaning a lack of means to cope without damaging loss. Loss can take many forms—becoming or being physically weaker, economically impoverished, socially dependent, humiliated or psychologically harmed."

In other words, Chambers distinguishes between an effective state of deprivation – poverty – and the *possibility* of being unable to cope with possible negative consequences in the face of external difficulties. Thus vulnerability, in a sense, refers to a future situation, the *potential* for an individual or a household to enter a difficult or undesirable situation. Consequently, poverty itself is not vulnerability; rather poverty can be a contributing factor, a part of the lack of means of being able to cope with the unexpected.

Chambers' distinction between "external" and "internal" vulnerability is extremely similar to the vulnerability frameworks in the environmental science where exposure is considered to be a component of overall vulnerability. If we draw parallels between Chambers' definition of vulnerability and those presented for instance in the frameworks of Cutter et al. (2003) and Turner II et al. (2003), we find a similar sort of process where there needs to be exposure to an external event or stressor, and the resultant consequences depend on the resources available to the actor in order to cope with the hazard. The main difference is principally the level at which everything takes place. In the environmental sciences the focus is usually on the regional level, while Chambers' definition focuses explicitly on the micro-level i.e. individuals and households. Nevertheless, certain frameworks in the environmental sciences, denoted as a "political economy approach" by Füssel (2007), are extremely similar in their conception of vulnerability. In this view, for vulnerability to be observable, there needs to be an external "impetus" which makes actors confront their conditions, and mobilize their resources to prevent damage or loss. Beyond this explicit approach to vulnerability, there are the related concepts of risk, precariousness/precarity, and social exclusion. We will start with the notion of risk which has become an important concept in the social sciences and has subsequently informed work on social exclusion and precariousness.

The concept of risk in the social sciences was popularized and spread by the work of Beck (1992). This broad and encompassing view of risk as a guiding element of the development of modern societies shares similarities with the integrated or social vulnerability approaches in the environmental sciences. Beck considers risk to be the "[...] probabilities of physical harm due to given technological or other processes" (Beck 1992, 4), and a "*systematic way of dealing with hazards and insecurities induced and introduced by modernization itself*" (Beck 1992, 21; emphasis in original). Beck's definition of risk has commonalities with the definitions of vulnerability in disaster studies and the environmental sciences. First, there is the notion of hazard which is an element shared with Chambers' definition of vulnerability as well as those in the environmental sciences. However, one important difference is that Beck does not use the concept of hazard in a manner that is consistent with vulnerability frameworks in the environmental sciences. In certain cases, for Beck (1992), the term hazard refers to potential damage in the aftermath of a stressor or event, and in others it refers specifically to something that causes damage. Another difference compared to vulnerability frameworks is that, for Beck, there is a persistent and pervasive stressor or external shock which is the process of modernization. It is not necessarily a punctual event that occurs at a specific point in time, rather it is a continuous process that can produce punctual events. The other aspect that is common is the "dealing with" which is analogous to coping. Therefore risk is something that can be acted upon, just as in the case of stressors related to the natural environment.

Nevertheless, Beck further expands his notion of risk by distinguishing between realized, or real, hazards and damages, and potential hazard and damages that can occur in the future. It is here that he incorporates the notion of potentiality that is more clearly visible in the definitions of vulnerability in disaster studies by stating that: "There must be a distinction between *already destructive consequences* and the *potential element* of risks. In this second sense, risks essentially express a *future* component. [...] By nature, then, risks have something to do with anticipation, with destruction that has not yet happened but is threatening [...]" (Beck 1992, 33; emphasis in original). Here we find the "potential for loss" described by most recent definitions in disaster studies and the environmental sciences. He further emphasizes the latent nature of risk or vulnerability which corresponds to Chambers' "internal" component of vulnerability. It is precisely this immediately intangible aspect of risk that is considered problematic by Beck as it requires establishing a discourse establishing the causality of the potential consequences of a hazard before it has occurred which requires a great amount of knowledge of the processes that can lead to damage.

This intangible nature of risk, but also the wide-reaching potential consequences of hazards, lead Beck to consider that risk leads to a new stratification of societies based on the degree of exposure to risk. Risks and hazards in Beck's view correspond to phenomena and consequences that go not only beyond geographical borders but also social ones. Nevertheless, Beck notes that differences in risk, or stratification by risk, overlap with existing forms of social stratification such as social class. Thus, individuals in more favourable positions can use their resources to insulate themselves, to a degree, from risks or prepare themselves better for the consequences than others.

While Beck's view of risk in society is very wide-ranging, pervasive, and applies to many domains, a more direct concern, nonetheless shared by Beck, in the social sciences is the rise of risk in relation to the transformation of the welfare state. Changes in the welfare state are particularly focused on in the study of risk especially in the field of sociology. The end of the "trente glorieuses" and the decline of economic growth, demographic shifts, labour market transformations, and seemingly the end of Keynesian economic policies, all which can be considered consequences of modernization, created a series of "new social risks" (Taylor-Gooby 2004) with which individuals have to contend. The expansion of the labour market with the increasing participation of women, an ageing population, a shift from manual occupations and unskilled jobs, and an increasing tendency towards the privatization of the welfare state introduce new risks which welfare states and individuals are not prepared for.

One of the main characteristics of "new social risks" according to Taylor-Gooby (2004, 8) is that individuals have to manage these new risks themselves more than ever:

> "Successfully managing new risks is increasingly important, particularly for the more vulnerable groups, since the risks themselves affect more people and because failure to cope with them successfully can have substantial implications for poverty, inequality, and future life chances."

In this description of new risks, we find elements that are common to definitions of vulnerability in the environmental sciences and disaster studies. Individuals have to "cope" with these risks, and in case of "failure" to do so, there is the possibility of experiencing damage or potential loss. There is also a reference to "vulnerable groups" but this is relatively vague. If we follow Esping-Andersen (2002, 14) as Taylor-Gooby does, these "vulnerable groups" are predominantly individuals that are on the margins of society and who are at risk of exclusion "such as single parents with small children, older workers, or people with disabilities."

The second aspect of these new social risks is that while these new risks affect more individuals than previously, they are not completely indiscriminate and continue to affect certain segments of society more than others which we also find in Beck's risk society perspective. For Taylor-Gooby (2004), they disproportionately affect younger individuals since social risks are considered to principally derive from one's labour market position and it is precisely the labour market that has gone through the most transformation. However, not everyone has the same chances of entering the labour market and finding a stable job and meeting their needs, and thus individuals who have less access to training and education, and/or who cannot rely on the state or family to help with difficulties with caring for children or the elderly are at an increasing disadvantage. Consequently new social risks go beyond traditional boundaries and enter domains which were previously considered private and which were not within the purview of the welfare state.

Similarly, Ranci (2010) builds on the perspective of risk and new social risks to construct a definition of vulnerability. Vulnerability is defined as follows: "[...] vulnerability identifies a situation that is characterized by a state of weakness which exposes a person (or a family) to suffering particularly negative or damaging consequences if a problematic situation arises." (Ranci 2010, 16) This definition is extremely similar to that of Chambers (1989) and is broadly similar to those in the environmental sciences.

Ranci considers that new social risks are a consequence of individuals being increasingly required to coordinate the demands of different domains on their lives on their own and with decreasing support from the welfare state. The pervasiveness of risk factors in relation to the rise of new social risks serves as the starting point for investigating vulnerability. While the risks are widely distributed, the negative consequences related to exposure to these risks isn't. This is precisely the domain of vulnerability in Ranci's view: "The more the risk factors diversify and the more difficult it becomes to predict the negative outcomes, the more central the dimension of vulnerability becomes in understanding the areas of social disadvantage." (Ranci 2010, 17)

A similar view is taken by studies of social exclusion where the end of the Fordist or Keynesian welfare state signals a new disparity in individuals' social integration in relation to the labour market (Paugam 2007) or in relation to individuals benefiting from social assistance programmes (Paugam 2009). In both cases, the focus is mainly on vulnerable individuals; that is those who are at the margins of society. Paugam's work (2007, 2009) on the labour market and social assistance incorporate an aspect of vulnerability missing from previous approaches: individuals' subjective evaluation of their situation.

Paugam (2009) distinguishes between three types of social exclusion which can be ordered, in a sense, by the degree to which individuals are outside of society. The first group are the "fragile" who, while being beneficiaries of social assistance, may be employed in precarious jobs, or are looking to return to employment. This group is principally characterized by people requiring punctual assistance in relation to financial difficulties, and being in precarious positions relative to opportunities for securing regular and sufficient income. Thus objectively, this group is possibly the least precarious or socially excluded, but subjectively they feel excluded, humiliated as if they don't meet the expectations society has set. Yet, they don't have to completely rely on social assistance, and they continue to have some level of autonomy and self-determination which becomes more limited for the next two categories: the "assisted" and the "marginals".

The "assisted" are individuals whose income depends on receiving social assistance as they may be unable to have gainful employment, or unable to provide for their children. This category seemingly corresponds to the vulnerable groups as defined by Esping-Andersen (2002) and Taylor-Gooby (2004). They are therefore considered vulnerable as they have to rely on other sources of income that are not derived from their own activities. Contrary to the fragile, the assisted rely much more on social assistance, but initially they share a similar objective which is to return to employment and to no longer have to rely on any form of assistance. Over time, however, individuals who don't manage to re-enter employment may become increasingly dependent on assistance and resign themselves to the necessity of living with assistance as the prospect of finding employment becomes increasingly daunting.

Finally, there are the "marginals" who have neither employment-related income nor income provided by social assistance programmes run by the state. These are the individuals that are most excluded from society, who are excluded from any safety nets, and who can only rely on charity or meagre incomes. These are individuals who may even be *beyond* vulnerable as they are not even helped by the welfare state. In a sense, they are in a position that the welfare state aims to prevent individual from entering as evidenced by the view of Esping-Andersen (2002) and Taylor-Gooby (2004) on vulnerable groups.

In the case of labour market integration Paugam (2007) distinguishes between four types of labour market positions related to both objective conditions and subjective conditions. This typology again combines objective employment conditions – in other words the contractual employer–employee relationship – with the subjective satisfaction with one's work.

The ideal situation – "assured" labour market integration – is one where employees have a stable contractual situation and are satisfied with their job. The three other categories of employment are considered "deviations" from this ideal situation. First there is "laborious" labour market integration which is characterized by stable employment but low job satisfaction. Second there is "uncertain" labour market integration where employment is unstable but job satisfaction is high. And finally, there is "disqualifying" labour market integration where employment is insecure *and* job satisfaction is low. For Paugam it is these last two forms of employment that are the most precarious. However, uncertain integration is not necessarily felt as being precarious as it can serve as a stepping stone to moving to assured labour market integration. Thus, this form of labour market integration can be considered as being less precarious than disqualifying integration as there is the possibility of an upward trajectory in the future.

The same cannot be said for disqualifying integration which is considered to be a precursor to social exclusion. It is a situation where instability is coupled with the perspective of a downward career trajectory and the possibility of entering unemployment in the near future. Thus, this is considered to be a precarious position because of the future potential of decline and social exclusion which again aligns with the vulnerable groups described by Esping-Andersen (2002) and Taylor-Gooby (2004).

What is common to these approaches of social exclusion and precariousness is that they focus on the position of individuals and the potential for certain individuals to end up in difficult situations without income, or the benefit of a safety net. This is further illustrated by Standing (2011) and his notion of "precariat" which designates a new "class" of individuals primarily defined by their lack of labour market security, job security, and often lack of identification with their employment; all characteristics that are common to "disqualifying" labour market integration in Paugam (2007).

The members of the precariat:

> "[...] can be identified by a distinctive structure of social income, which imparts a vulnerability going well beyond what would be conveyed by the money income received at a particular moment. [...] They are more vulnerable than many with lower incomes who retain traditional forms of community support and are more vulnerable than salaried employees who have similar money incomes but have access to an array of enterprise and state benefits. A feature of the precariat is not the level of money wages or income earned at any particular moment but the lack of community support in times of need, lack of assured enterprise or state benefits, and lack of private benefits to supplement money earnings." (Standing 2011, 12)

We once again end up with our vulnerable groups; that is individuals who in the face of difficulties have no recourse or access to resources in times of need and therefore that's what makes individuals in the precariat vulnerable. In a sense, here vulnerability is considered to be a state where the potential for social decline is substantial. This view is less clearly explicit than the definitions that are generally used in disaster studies as vulnerability is latent, or even secondary. Moreover, the focus is more on identifying individuals and groups susceptible to finding themselves in a situation where their employment could lead to them not receiving the resources they need in difficult times.

Misztal (2011) proposes a more general framework, or an "aggregative conception" (Misztal 2011, 49–50), of vulnerability that attempts to combine elements of vulnerability frameworks in the environmental sciences, the concept of risk, and the "new social risks" perspective. She distinguishes between three forms or classes of vulnerability: "dependence on others, the unpredictability of the future and the irreversibility of the past." The first form of vulnerability refers to the interdependent nature of human existence which means that people's decisions often depend on others around them. Individuals are not always able to live their lives by depending entirely on their own abilities or resources. As such vulnerability is in a sense a measure of how much someone is required to rely on others in order to meet their needs which in turn exposes them to abuse or being taken advantage of. This form of vulnerability seems to be close to that of Taylor-Gooby (2004) or Standing (2011) in the sense that their implicit view of vulnerability often refers to individuals that would be unable to support themselves in times of difficulty.

The second form of vulnerability – unpredictability – is closest to the Beck's (1992) notion of risk, and is very close to vulnerability as it is conceived in disaster studies. Fundamentally, this form of vulnerability is related to the impossibility of being able to predict everything that could possibly occur in the future that may put someone in a difficult position. In this situation vulnerability therefore corresponds to the ability to deal with an unexpected future event and the resources available to do so.

Misztal's third form of vulnerability departs from most of the previous definitions. It concentrates on the consequences of past experiences that are permanent or that can't be recovered from and that cause lasting damage or trauma. This form of vulnerability mainly refers to emotional scarring caused by past events.

This trauma may prevent individuals from accomplishing their goals and escaping past difficulties and problems. Thus, this form of vulnerability refers to individuals' difficulties in recovering from past consequences inflicted upon them by others and moving on from them and taking control of their lives and their future.

Finally, I will briefly introduce vulnerability in relation to the stress process models, and approaches to social stress which will be further detailed in Section 3.3. The work on social stress seeks to understand, most often, differences in the prevalence of depression or other psychological disorders in the general population (Aneshensel 1992). For Kessler (1979, 101), and indeed a large part of the literature on social stress, vulnerability simply refers to individuals' likelihood of experiencing a decline in their mental health when exposed to a stressor, or "[. . .] the force with which a stress impacts the distress of an individual." Thus vulnerability is the measure of negative consequences, or the increase in distress, experienced by an individual in the face of a stressor.

One of the main concerns in the study of stressful events and the relationship with psychological distress is the link between exposure to stressful events and the likelihood of experiencing psychological distress (Kessler and McLeod 1984; Kessler et al. 1985). Certain individuals are more likely to be exposed to stressful events that, on average, more often lead to psychological distress. Another concern is identifying other individual factors that influence vulnerability to depression or distress (Kessler 1997). These "vulnerability factors" are often related to social resources, past experiences, individuals' environment, and other less tangible resources such as coping strategies, personality traits, or certain possible genetic predispositions. Fundamentally, a relatively simple model underpins this approach to the study of vulnerability which is to compare differences between groups in the level of depression after experiencing stress. Vulnerability factors are considered to modify the relationship between exposure to sources of stress and the development of depressive symptoms.

While taking a similar approach, Pearlin and colleagues (1981; 1989; 1990; 2010) develop a more extensive framework initially drawing on path models. Vulnerability is again – implicitly – defined to refer to the susceptibility of experiencing symptoms of psychological stress or depression. In its basic form (Pearlin et al. 1981), this model posits that a disruptive event will have an impact on the change in the level of depression. Where this model offers a more substantial contribution is in the incorporation of multiple resources or attributes that can mediate the adverse events.

Another aspect of the stress process model that is distinct from most social science approaches to vulnerability – but is present in approaches in the domain of the environmental sciences – is the notion of repeated sources of stress or "chronic strains". A further extension (Pearlin 1989) is the notion of primary and secondary stressors as it is often unlikely that individuals are confronted by only one source of stress at a given time. Rather sources of stress tend to snowball and potentially create other sources of stress that can afflict individuals later on. Finally, this framework analyses *manifest* outcomes, i.e. it applies to vulnerability that is observed and not necessarily latent.

3.1.3 Summary

Through all these definitions of vulnerability or risk, we see one common element which is that they all try to apprehend and measure the potential negative consequences or harm that can result from the exposure to a stressor, or an event that is potentially destructive and difficult to deal with. Where the definitions vary is their use of related concepts such as risk or resilience. In certain frameworks, notably those in the environmental sciences or human geography approaches, risk and resilience are often considered to be components or elements of vulnerability rather than distinct from it.

In other cases, most notably the social sciences, there is often significant overlap between the concepts of risk and vulnerability. The most telling case is Beck (1992) and his notion of risk which encapsulates not only the possibility of being confronted by a hazard derived from processes of societal change and development, but also the potential for destruction in the future from these hazards. Another aspect that emerges in the social sciences is that vulnerability is often employed in an implicit manner. In the case of the literature on social exclusion or social risks, there are references to "vulnerable groups" which most often correspond to single-parent families, individuals in non-standard or precarious employment, or those at risk of poverty for instance.

However, in most definitions proposed by the social sciences (especially those that focus on "vulnerable groups"), there is a lack of an explicit time dimension of vulnerability. There is, in a sense, a focus on the *occurrence* of negative consequences, but not necessarily the process leading up to these consequences, nor the process of attempting to recover from them. This is not only the case for the environmental sciences, but also for the stress model processes that form the basis of the dynamic approach proposed by Spini et al. (2013) and Spini et al. (2017).

3.2 Terminology: Vulnerability vs. Risk vs. Resilience

In the overview of how vulnerability can be defined in Section 3.1, the terms vulnerability and risk were used almost interchangeably while the relationship between the concepts of vulnerability and resilience was more ambiguous. In this section, the relationship between these three concepts, and their use in the rest of this thesis, will be clarified. The aim is to be able to more clearly incorporate these somewhat ambiguous concepts in a vulnerability-as-a-process framework as will be presented in Section 3.3.

Vulnerability and risk often tend to refer to the possibility of an event leading to harm. However, in the environmental sciences, risk and hazard are sometimes used interchangeably. In the view of Kasperson et al. (2005, 253), risk can be defined as "the conditional probability and magnitude of harm attendant on exposure to a perturbation or stress." Risk can also be considered as being a *component* of vulnerability as is the case in Chambers (1989). Here, risk will be considered as being a necessary *condition* for the *manifestation* of vulnerability and will refer to the chances of a potentially damaging event occurring (Vatsa 2004; Aven 2011; Brüderl et al. 2019).

Risk in many vulnerability frameworks refers to the chances of a certain unit (individual, household, etc.) experiencing an event that can lead to loss. In this sense risk measures the likelihood of an event that can upset the status quo occurring. The focus is on the event itself and not the potential consequences. For example, individuals are at risk of experiencing divorce. However if we consider a negative outcome such as depression, not everyone is necessarily vulnerable after a divorce. For certain individuals divorce may be an emancipatory event that improves their quality of life while this might not be the case for others.

Risk doesn't determine individuals' latent vulnerability or innate propensity to experience negative outcomes. There may be individuals that are extremely vulnerable and who would experience severe depression, for instance, but manage to go through life without experiencing an adverse event that would trigger a negative outcome. This is where the debate on differential exposure in the (social) psychology literature on vulnerability and stress comes into play. We may perceive certain socioeconomic groups as being more vulnerable as they are more often subject to sources of stress; that is they have a greater risk of experiencing stressful events. Thus, having a greater risk of experiencing a stressor will usually increase individuals' vulnerability, but risk doesn't *cause* vulnerability nor does a low level of risk correspond to a low level of vulnerability.

This shows us that it is not necessarily easy to determine vulnerability in advance. In Sections 3.1.1 and 3.1.2, many authors point out the *latent* nature of vulnerability. That is, the fact that it's not necessarily possible to determine for a specific individual the likelihood of experiencing negative consequences, but also the risk of being exposed to sources of stress. As will be discussed in more detail in Section 3.3, the resources individuals have at their disposal can be one manner to quantify and identify potential vulnerability, to establish whether or not they are more or less likely to experience negative consequences when exposed to stressors.

However, the other element that makes vulnerability latent is that it is also dependent on risk, or exposure. That is, for vulnerability to manifest itself, there needs to be exposure to a source of stress without which vulnerability – i.e. negative consequences – will not be encountered (Oris 2017). An individual with very few resources, who may typically considered vulnerable, may never experience negative consequences if she or he is never exposed to a substantial source of stress. Thus, vulnerability can be dormant until there is a situation which challenges the status quo and which would require a change, a coping strategy in order to deal with the implications of the stressor.

Consequently, in order for vulnerability to be realized, or observed, there is an interplay between resources and exposure to sources of stress that leads to its manifestation. This rejoins with view of Chambers (1989) and the distinction between internal and external vulnerability as well as the definition of vulnerability formulated by Turner II et al. (2003). Moreover, as will be further expanded in Section 3.3, resources and exposure to sources of stress are not mutually exclusive as resources can be used to prevent the occurrence of stressors or avoid them altogether.

The manner in which the two – exposure and resources – can be linked most obviously is that having a high risk of experiencing a certain stressor also means that the chances of *repeatedly* experiencing the stressor, or it being chronic, are higher. This reduces the time available for individuals to accumulate resources and recover from the negative consequences of a stressor. However, the reverse is not necessarily true. Individuals with a low risk of experiencing a stressor are not necessarily less vulnerable. Even if they had almost no chance of experiencing a stressful event, they may be just as likely to experience significant loss.

Thus, while vulnerability and risk are related, risk is not necessarily a component of vulnerability. Risk as it is conceived in this thesis concentrates on what determines the occurrence of events and stressors that can lead individuals to experience loss, the potential triggers that can cause vulnerability to manifest. This is contrary to vulnerability which itself focuses on the "fallout" or the consequences for the unit of study after experiencing a stressor. The absence of risk may signify the absence of vulnerability manifesting itself, but it doesn't necessarily signify the absence of vulnerability.

This separation of risk from vulnerability is similar to the separation Ranci (2010, 17) makes between hazard, "the probability of a potential negative situation occurring", and vulnerability, "the degree of exposure to damage that may result from the situation", in relation to social risks. This same distinction is also made by Brüderl et al. (2019) where risk analysis is considered to focus on the occurrence of the event, while the analysis of vulnerability focuses on (life course) outcomes in the face of an adverse event. Therefore, the main consideration of vulnerability is on what happens *after* an event and individuals' trajectories for a specific negative consequence. The main consideration in terms of risk is the analysis of what makes individuals more likely to be subject to a stressor or an adverse event.

The distinction between resilience and vulnerability, on the other hand, is less clear and is subject to a substantial amount of debate in the environmental sciences (Carpenter et al. 2001; Hufschmidt 2011). A very early definition of resilience is given by Holling (1973, 14) and is defined as: "a measure of the persistence of systems and of their ability to absorb change and disturbance and still maintain the same relationships between populations or state variables." Similarly, Walker et al. (2004, 2) consider that "[r]esilience is the capacity of a system to absorb disturbance and reorganize while undergoing change so as to still retain essentially the same function, structure, identity, and feedback." This view of resilience fundamentally suggests that in the face of a stressor, resilience implies that an entity is able to minimize the damage while also adapting to the situation in a way that limits possible disruptions. For Walker et al. (2004), resilience comprises four aspects: latitude, resistance, precariousness, and panarchy. The first refers to the amount of change that can be tolerated before recovery becomes impossible. The second aspect concerns the ability to avoid change altogether while the third refers to how close a system is to a limit or a point from which it would be difficult to recover. The final aspect is related to cross-level interactions and as such resilience is also dependent on wider scale aspects.

A similar view of resilience can also be found in psychology. Bonanno (2004, 20) for instance considers that resilience "reflects the ability to maintain stable equilibrium." Thus, individuals are resilient if, in the face of a source of stress, they are able to cope without a period of recovery. In fact, resilience is viewed as being in opposition to recovery by Bonanno and not necessarily as an individual's ability to mobilize resources to respond to stress. Nevertheless, resilience doesn't necessarily refer to the absence of *any* consequences. Rather, there may be some consequences but they are kept under control enough that they don't have a major influence on functioning. However, this definition is distinct from most approaches to resilience in the environmental sciences as it precludes recovery as being a form of resilient response (McFarlane and Yehuda 1996; Roisman 2005).

On the other hand, there are definitions of resilience that explicitly involve the conception of adaptation or adaptive capacity. Adger (2006, 268–269) for instance defines resilience as "the magnitude of disturbance that can be absorbed before a system changes to a radically different state as well as the capacity to self-organise and the capacity for adaptation to emerging circumstances" in opposition to vulnerability which is the susceptibility to be harmed. Similarly Folke (2006, 259) considers that resilience is not only "[. . .] about being persistent or robust to disturbance. It is also about the opportunities that disturbance opens in terms of recombination of evolved structures and processes, renewal of the system and emergence of new trajectories. In this sense, resilience provides adaptive capacity [. . .]". The same is true for Carpenter et al. (2001, 766) who consider that "[a]daptive capacity is a component of resilience that reflects the learning aspect of system behavior" when faced with adversity. The consideration that capacity to adapt is an element of resilience, or is synonymous with resilience as Smit and Wandel (2006) do, isn't necessarily always the case. Walker et al. (2004, 3) for instance state that "[a]daptability is the capacity of actors in a system to influence resilience", while Gunderson (2000, 435) defines adaptive capacity as "[. . .] system robustness to changes in resilience." Consequently, adaptability in this view is *external* to resilience and describes the changes that can be made to influence the components or elements of resilience in order to better deal with exposure to a stressor or adverse event.

Regardless of whether the capacity to adapt is an internal or external element of resilience, it is a key aspect in explaining potential ways in which systems or individuals can modify or change their functioning in order to minimize potential damage. As such, resilience is most often viewed as being the opposite of vulnerability, as the manners in which it is possible to prevent negative consequences or to more quickly recover and deal with potential negative consequences. As we'll see later, in modelling vulnerability as a process, the distinction is principally between *trajectories* of vulnerability and those of resilience and/or recovery.

To summarize, vulnerability, risk, and resilience are interrelated but distinct concepts. In the rest of this thesis, these concepts will be defined according to the following minimal definitions:

Vulnerability The likelihood of an individual (or household, or other unit of study) will experience negative consequences when exposed to an adverse event.

Risk The chances an individual (or household, or other unit of study) will be confronted by an adverse event that has the potential to create negative consequences.

Resilience The ability of an individual (or household, or other unit of study) to cope with negative consequences either by minimizing them or by recovering from them.

3.3 Vulnerability as a Process

The starting point for the dynamic view of vulnerability proposed by Spini et al. (2013) and Spini et al. (2017), which is the one adopted here, is the stress process model from Pearlin et al. (1981) and Pearlin (1989). In the stress process model, vulnerability is most often associated with a decline in an individual's mental or psychological state. This model aims to describe the mechanisms that lead to such a decline or "negative consequences". The main element is the exposure to sources of stress which can be specific punctual events, also called *life events*, or smaller recurring problems also termed *chronic strains*.

Beyond just exposure to sources of stress, Pearlin (1989) argues that another aspect that needs to be taken into account is the perception of stressors. Certain individuals may view a stressor as being less of a threat than other people would, even if the stressor is the same. This may possibly lead to a stressful event not being perceived as such and thus not necessarily leading to negative consequences or outcomes.

Furthermore, Pearlin argues that sources of stress are not necessarily independent and that there may be multiple stressors operating at once. Some may possibly be unobserved and certain sources of stress may be more prominent or important than others. Thus, focusing on a single source of stress may lead researchers to omit the interplay of multiple stressors on differences in outcomes between individuals when exposed to similar sources of stress.

The second element in the stress process model is resources, or to use the terminology of Pearlin et al. (1981) and Pearlin (1989), "mediators". These resources are considered to play an essential role in explaining differences between individuals concerning outcomes or the manifestations stress. The two main resources considered by Pearlin are coping and social support. Coping refers to the individual strategies and actions taken by individuals to lessen the changes or impact of the stressor on their lives. Social support is seen as a manner in which individuals draw on the social resources they have available to them, or at least a subset, which would allow them to better deal with the difficulties brought about by sources of stress.

The final element is the outcomes associated with sources of stress. There are numerous outcomes that can be considered such as psychological distress, health, or depression. However, Pearlin (1989) also argues that in certain cases taking a multidimensional approach to analysing outcomes may be necessary. Different sources of stress don't necessarily lead to the same outcome for all individuals. In the study of vulnerability, the choice of stressor can lead to different conclusions regarding an individual's vulnerability. One source of stress can lead to negative consequences for one individual, but not for another and vice versa. This can lead to the conclusion that certain groups are more vulnerable due to a higher likelihood of experiencing negative consequences than others simply by focusing on one specific source of stress instead of another.

Beyond these three elements, Pearlin (1989) stresses the importance of (social) context. Individuals' exposure to sources of stress, their perception of stress, as well as their resources all depend on the context in which they find themselves. Context plays an essential role in explaining potential differences not only at the level of exposure, but also the potential outcomes individuals experience when faced with sources of stress. Context is considered to play a role in all aspects of the stress process.

Building on Pearlin's stress process model, Spini et al. (2013, 19) and Spini et al. (2017) propose the following definition of vulnerability:

> [. . .] a lack of resources, which in a specific context, places individuals or groups at a major risk of experiencing (1) negative consequences related to sources of stress; (2) the inability to cope effectively with stressors; and (3) the inability to recover from the stressor or to take advantage of opportunities by a given deadline.

This definition is the basis for the analysis and operationalization of vulnerability in this thesis.

There are multiple elements in this compact, yet broad, definition that need to be more closely examined and developed. The first is the notion of a lack of resources. As we have seen in previous sections, the concept of resources or the availability of resources is extremely present in the study of vulnerability. However, what these resources *are*, which ones to consider, and how they operate to protect individuals from vulnerability is less clear.

The second aspect is the notion of "specific context". The idea here is that a lack of resources is not the only thing that matters in explaining vulnerability. The effect of resources varies according to the situation individuals may find themselves in, the social context in which they live. Thus, a lack of resources will not necessarily lead to the same outcomes depending on the context.

And now, we come to the core of the vulnerability process. Vulnerability is divided into three stages here: experiencing negative consequences, the inability to cope, and the inability to recover. These three stages are considered to be the consequences of an individual, or group, experiencing a stressor or adverse event.

In this section, these aspects will be further detailed and expanded with the goal of establishing a potentially more precise, but less encompassing, definition of vulnerability that will be linked to the 2008 Financial Crisis and the methodological applications in Chapters 6 and 7.

Resources

Resources can take many different forms and come from varying domains. Spini et al. (2013) consider that resources principally belong to one of three groups: biological, psychological, and socioeconomic. Biological differences between individuals can influence their developmental processes which can have a knockon effect in individuals' lives in the future. However, it is not only in early life that such resources can play a role. In older life as well, biological or genetic resources matter but their role is less well understood. Thus, individual biological characteristics can be considered as a resource which can potentially explain differences between individuals especially at a very young age, but potentially also as people get much older (Baltes et al. 2006). Nevertheless, in the context of vulnerability, be it in the social or psychological sciences, the incorporation of biological resources is less evident and the role played by these resources in adulthood is comparatively less investigated (Baltes et al. 2006, 575; Spini et al. 2017).

When it comes to resources in the psychological domain, Hooker and McAdams (2003) (see also McAdams 1995; Hooker 2002), identify three levels or types of resources related to individual personality: traits, self-regulatory processes, and "life story" or identity narratives. The first type, traits, for example measured using the Big-Five framework (McCrae and John 1992; Goldberg 1993), are often considered to be more or less fixed. They are thought not to vary over time, and describe almost ingrained aspects of personality that individuals can draw on in their lives. This is not a dynamic resource and is not particularly context dependent either (McAdams 1995; Hooker 2002; Hooker and McAdams 2003), though studies have shown that traits are not necessarily completely stable and do shift over time especially as people age (Roberts et al. 2003). Nevertheless, personality traits are most often considered to be stable non-varying attributes and resources. Personality traits, can also be considered to overlap with existing biological resources as they can be considered as an expression of individuals' genetic traits (McGue et al. 1993; Jang et al. 1996; Vernon et al. 2008; Bouchard Jr. and McGue 2003; Power and Pluess 2015) and therefore are also related to the biological domain.

This is in contrast to the second type, self-regulatory processes. These are individuals' strategies and methods for coping, their personal goals, or what individuals aim to achieve in relation to their personal situation. This type of resource is one that is developed over the life course and is dependent on individual contexts and experiences. These resources develop over time and change along with individuals and their goals.

The final type, identity narratives, serves to help individuals draw on past experiences and position themselves relative to the situations which they face. These experiences can be a resource in that they allow for self-reflection, and for individuals to adapt to their current situation based on previous experiences. In studies of psychological vulnerability, the focus has principally been on resources of the first two categories: traits and self-regulatory processes (Hanappi et al. 2015).

In the case of socioeconomic resources, the notion of resource is potentially very broad. On the one hand, there are more tangible, material, resources such as income or wealth and on the other, less tangible resources such as socioeconomic status, social support, social networks or education. These socioeconomic resources have become increasingly important in the analysis of vulnerability especially in disaster studies, as evidenced in Section 3.1.1. The most common manner of measuring tangible socioeconomic resources is the use of monetary or financial indicators such as income, wealth, or expenditure (Lucchini and Assi

2013). An extremely common measure for a lack of resources is the use of the relative poverty measures which consider that households have a lack of resources if their equivalized household income is below 60% of the median income in a specific country (Nolan and Whelan 2010).

However, non-monetary indicators can also be used to assess resources. In the case of disaster studies, access to adequate housing for instance is an indicator of access to resources. The multiple deprivation research strand often employs multiple indicators related to the consumption or access to certain material goods. In this framework, the indicators are more often quite granular and numerous.

Thus, rather than simply look at the availability of purely monetary or financial resources, multiple deprivation approaches attempt to assess that lack of resources through the unavailability of certain services or possessions. For example, in their analysis of economic vulnerability in Europe, Whelan and Maître (2010), operationalize deprivation using multiple indicators notably being unable to go on holiday, pay for unexpected expenses, not having a computer, or being unable to afford a car among other indicators. However, this unavailability needs to be imposed and not be intentional as individuals or households who choose to forego certain things willingly cannot necessarily be considered as lacking in resources.

On the less tangible, or non-material side, an important and often investigated resource is education. It is considered to be crucial especially in the literature concerning vulnerability for instance in relation to health outcomes (Frytak et al. 2003; Mirowsky and Ross 2003; Zajacova and Lawrence 2018) or employment outcomes (Becker 1994; Pallas 2003; Gesthuizen and Scheepers 2010). Education can also serve to help individuals find resources that are available to replace ones that may be unavailable or inadequate at a certain point in time and thus help in finding substitutes (Mirowsky and Ross 2003, 18). Education, beyond being a resource in itself, can also serve as a marker of possession of other resources, notably cognitive, which would allow individuals to better navigate difficult situations. Other socioeconomic resources, such as (social) support, also play a role in complementing or substituting a lack of personal resources by drawing on the resources of others (Pearlin et al. 1981; Gesthuizen and Scheepers 2010; Wegener 1991).

Beyond just the types of resources available, there is also a time dimension that needs to be taken into account. Different individuals will accumulate a different amount of resources over time. Moreover, the accumulation of resources in the past can lead to differences in the accumulation or the availability of resources in the future. This is expressed by the cumulative (dis)advantage framework which posits that differences in resource accumulation over the life course is compounded by previously existing differences (Dannefer 1987; Crystal and Shea 1990; O'Rand 1996; Dannefer 2003; see also Merton 1968). That is, individuals who at a certain point in time had more resources than others, will at a later point in time have comparatively gained more resources than others thus increasing differences between individuals.

Another aspect of the time dimension is that certain resources may not actually be available or useful until a later date. In the context of individual life courses, Cullati et al. (2018) suggest that these types of resources can be considered as *reserves*. In their view, the main distinction is that reserves are not an immediately available resource. They only become a viable resource as they accumulate over time and are often unable to help individuals deal with everyday necessities or would take too long to mobilize to be useful in the short-term. In this sense, reserves can be considered as “potential means”, or “latent capability” (Cullati et al. 2018, 552).

In addition, reserves are dependent on the availability of other resources. To constitute reserves, the resources available to an individual at a certain time must not only cover their daily needs, but actually exceed them. This allows these excess resources to be set aside and be called upon in the future when the immediately available resources may be insufficient to deal with a specific situation.

This leads to the third characteristic of reserves: their protective function. Contrary to more general resources, reserves primary use is not to satisfy immediate needs or to ensure daily functioning. Reserves are principally called upon in times of need usually when there is a change that perturbs the lives of individuals which cannot be dealt with using “regular” resources.

As we can see, the concept of resources is broad but also multidimensional as resources can come from many different domains. Resources are not necessarily exclusive to specific domains as there can be overlaps between different types of resources as was shown in the case of personality traits for instance. Specific type of resources, such as socioeconomic resources, can also be composed of many sub-resources. Moreover, in the case of socioeconomic resources, these sub-resources can be of different types as it is possible to distinguish between material and non-material resources. And finally, there is the dimension of time as resources are not necessarily stable and can evolve and change. This further emphasizes the need to take a dynamic approach in the study and modelling of vulnerability.

Context

The second aspect of the definition is the notion of “specific context”. The context in which an individual lacks resources will also determine their vulnerability. One line of enquiry is the analysis of the role of the welfare state, or different welfare regimes (Esping-Andersen 1990, 1999), on vulnerability (Whelan and Maître 2010; Gesthuizen and Scheepers 2010; Whelan et al. 2013). As we saw with Taylor-Gooby (2004), one major role of the welfare state is to redistribute resources to those who have the least. Therefore, in the case of a lack of resources the redistributive function of the welfare state can reduce the lack of resources, or through services, prevent the exposure to negative consequences even if there is a lack of resources.

Nevertheless, the arrangements and redistribution of resources vary among different types of “welfare regimes” (Esping-Andersen 1990, 1999). Following the typology of Esping-Andersen(1990, 1999), certain welfare regimes, such as the conservative welfare regime (exemplified by Germany) may, transfer fewer resources to certain individuals than others. This is because the focus is on helping certain segments of the population, traditionally male breadwinners, rather than other individuals who may be in even more precarious situations. This is in contrast to countries belonging to the social democratic regime (typically the Nordic countries) where the welfare state aims to provide similar coverage and resources to all individuals regardless of their socioeconomic circumstances.

However, the transformation of the welfare state in more recent times has further changed the context in which individuals have to deal with sources of stress. Even if there remain differences between different countries' welfare systems (Esping-Andersen 1990), according to Esping-Andersen (1999) there is an overarching trend towards welfare state retrenchment especially in the case of more liberal welfare regimes which includes countries such as the UK or the US. This progressive erosion of the welfare state is accompanied by a reduction of protection given by the state and a shift to greater individual responsibility (Beck 1992; Esping-Andersen 2002, 4; Ranci 2010; Oris et al. 2016). This has increasingly shifted the burden from the state to individuals who must mobilize their personal resources more often in order to meet the requirements set by countries to allocate them additional resources in times of need. Even the Nordic countries, who traditionally had a more protective and encompassing welfare state, are also shifting towards putting more responsibility on individuals themselves (Kvist et al. 2011, 204). In part, this shift is presented as a necessity, even in countries with traditionally strong welfare regimes, in order to guarantee employment and to ensure they are able to continue financing social assistance programmes.

Related to this, is the role of welfare states in reducing or exacerbating economic inequality in general (Esping-Andersen 1990, 23–24; 1999, 132–133). Generally, liberal countries such as the UK or the US are characterized by higher levels of inequality, especially in relation to income, than the conservative, or Continental European, and Scandinavian welfare regimes. This is also important to consider as economic inequality can play an important role in influencing individual vulnerability. A less equitable distribution of resources, primarily economic, decreases the possibility of dealing with hazards for a potentially large proportion of society. Consequently, highly unequal societies concentrate a large part of the resources in the hands of a few, drastically reducing the possibility of dealing with sources of stress for everyone else (Van de Werfhorst and Salverda 2012). Thus, contextual factors can play a very important role in the relationship between sources of stress and the outcomes individuals experience.

However, context does not completely determine the resources or strategies available in dealing with sources of stress or coping. While context can play a major role in helping or preventing individuals from dealing with sources of stress, there continues to be individual agency and other inter-individual differences in strategies, personal experiences, or even personality, if we consider psychological resources. This can allow individuals to potentially make the best of an adverse situation in certain situations, while this may not be the case for others.

Beyond the larger socioeconomic context, there is also individuals' more immediate context. Compared to the larger context such as the general economic context or the type of welfare state, "meso"-level contextual elements have a greater proximity to individuals and they can potentially interact with them in person. For instance, the neighbourhood or area in which people live can determine access to services and other resources which can be used to help deal with sources of stress (Kirby and Kaneda 2005; Mechanic and Tanner 2007; Curley 2010; Small 2014). While there may be some overlap between context and socioeconomic resources – especially resources such as social support – the main distinction is that individuals have less of a direct influence on, and relationship with, contextual elements compared to resources. Contextual elements are therefore not part of individuals' immediate social circle nor do they have a direct access to these elements unlike with resources.

In the stress process framework (Pearlin 1989), individuals' context is considered to be vital in explaining differences in vulnerability. Individuals' roles and positions in the social fabric are shown not only to influence outcomes related to vulnerability but also exposure to sources of stress (Turner and Noh 1983; Kessler and McLeod 1984; Aneshensel 1992). While certain sources of stress may be exogenous or independent of the context, in many cases the sources of stress to which individuals are exposed can be a consequence of their social environment and the roles which are ascribed to them. This may be particularly relevant in the case of sources of minor but recurring stress which are more likely to be consequences of an individual's context.

In summary, in the case of vulnerability, taking into account context is extremely important and should not be ignored. It plays a role in determining which resources are available, the degree of exposure to stressors, or the expectations placed upon individuals or households in relation to overcoming sources of stress. Nevertheless, it doesn't completely determine how individuals will use the resources at their disposal or other strategies to deal with a potential lack of certain resources in the face of sources of stress (Schröder-Butterfill and Marianti 2006). Therefore, it is entirely possible that individuals in similar situations, and similar contexts with similar resources can experience different outcomes when faced with a source of stress. There remains a part of individual agency and unmeasured, or potentially unmeasurable, resources that continue to play a role in experiencing and responding to sources of stress.

Trajectories

The final major aspect of this definition is the trajectory followed after experiencing a source of stress while also being faced with a lack of resources. The first part of the process is experiencing negative consequences. If someone is in a situation of exposure to a source of stress and effectively in a position where there are inadequate resources to deal with this event, the first stage of vulnerability is experiencing a non-negligible deterioration of one's situation.

If no negative consequences are experienced despite a worsening of one's situation, this would be considered as a demonstration of resilience or lead to a trajectory of resiliency. However, resilience need not be limited to a case where there are *no* negative consequences experienced. In a broader sense, and in accordance with the definitions laid out on page 53, resilience can be thought of as a measure of the capacity to limit damage and thus avoid negative consequences which can impair individuals' functioning.

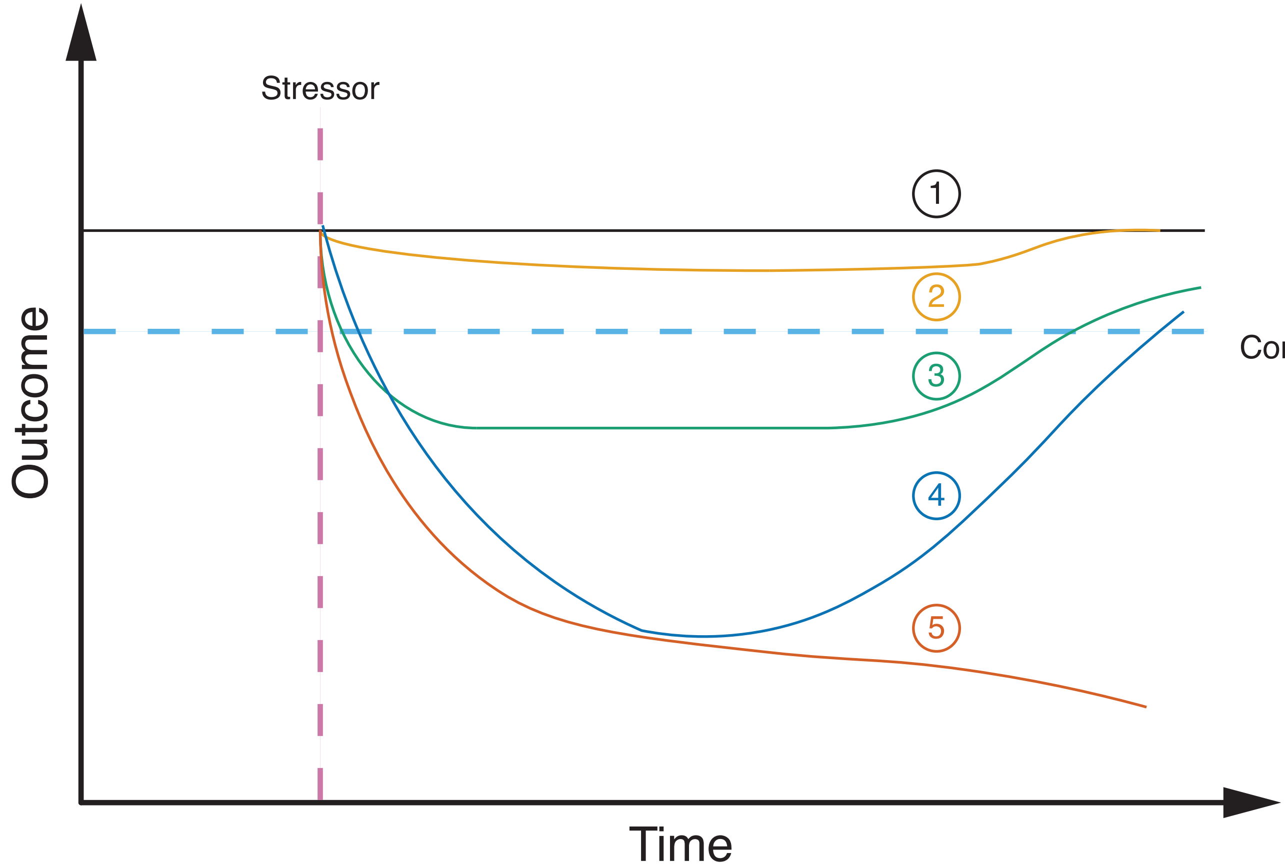

Figure 3.1 – Potential Trajectories of Vulnerability

If we consider a visual representation of trajectories of vulnerability, as in Figure 3.1, the first phase of experiencing negative consequences should occur immediately in the aftermath of the occurrence of the stressor. A non-vulnerable trajectory would correspond to the first one where the line stays flat and no change, or negative consequences are experienced. A resilient trajectory could be characterized by the second line where there is some decline in the short-term, but it never crosses the threshold of negative consequences. In the long-term there is nevertheless a gradual recovery. These are trajectories that do not demonstrate vulnerability as neither leads to any negative consequences.

The third trajectory is the first that is one that demonstrates vulnerability in the short-term. In this trajectory, the individual does experience negative consequences as a result of exposure to a source of stress. However, this trajectory demonstrates the ability to cope with consequences of the source of stress as the decline is eventually limited in the relative short-term. Coping therefore refers to individuals' ability to limit the impact of the negative consequences. In the long-term there is a trajectory of recovery and a return to a situation where an individual would no longer experience negative consequences.

The fourth trajectory shows an individual experiencing negative consequences, but also being unable to cope with stressors in the short-term while eventually recovering and no longer experiencing negative consequences in the long term. Compared to the third trajectory, the fourth demonstrates a greater vulnerability as there is no coping in the short-term, and the path to recovery is longer and slower. Consequently this could be considered as being a more vulnerable trajectory in the aftermath of experiencing a stressor.

Finally, there is the fifth trajectory which incorporates all the elements: experiencing negative consequences, being unable to cope, and finally not recovering after exposure to the source of stress. This is the most vulnerable trajectory as even in the long term, there is no perspective of an improvement or a return to the pre-stressor situation in this case. These trajectories are, of course, potential theoretical ones but they nevertheless illustrate different possible trajectories that could be experienced by individuals after being exposed to a source of stress. The different trajectories can be taken as evidence of differing resources available to respond to a stressor and minimize or prevent any subsequent negative consequences.

Putting it All Together

Taking everything together, vulnerability is a multidimensional and temporal process that occurs in the presence of a source of stress. Figure 3.2 summarizes the vulnerability process. The resources available to individuals can allow them to respond to the sources of stress. They can also play a role in determining whether or not individuals are even potentially exposed to sources of stress. Resources can serve to shield individuals from exposure to sources of stress in the first place while a lack of resources may possibly increase the chances of exposure to stress. For instance, those who know that their employer will be restructuring in the near future and expect to lose their job can use their contacts to avoid the situation entirely by finding a new job in advance. Yet, there are also sources of stress, such as environmental hazards, that can potentially affect everyone regardless of the

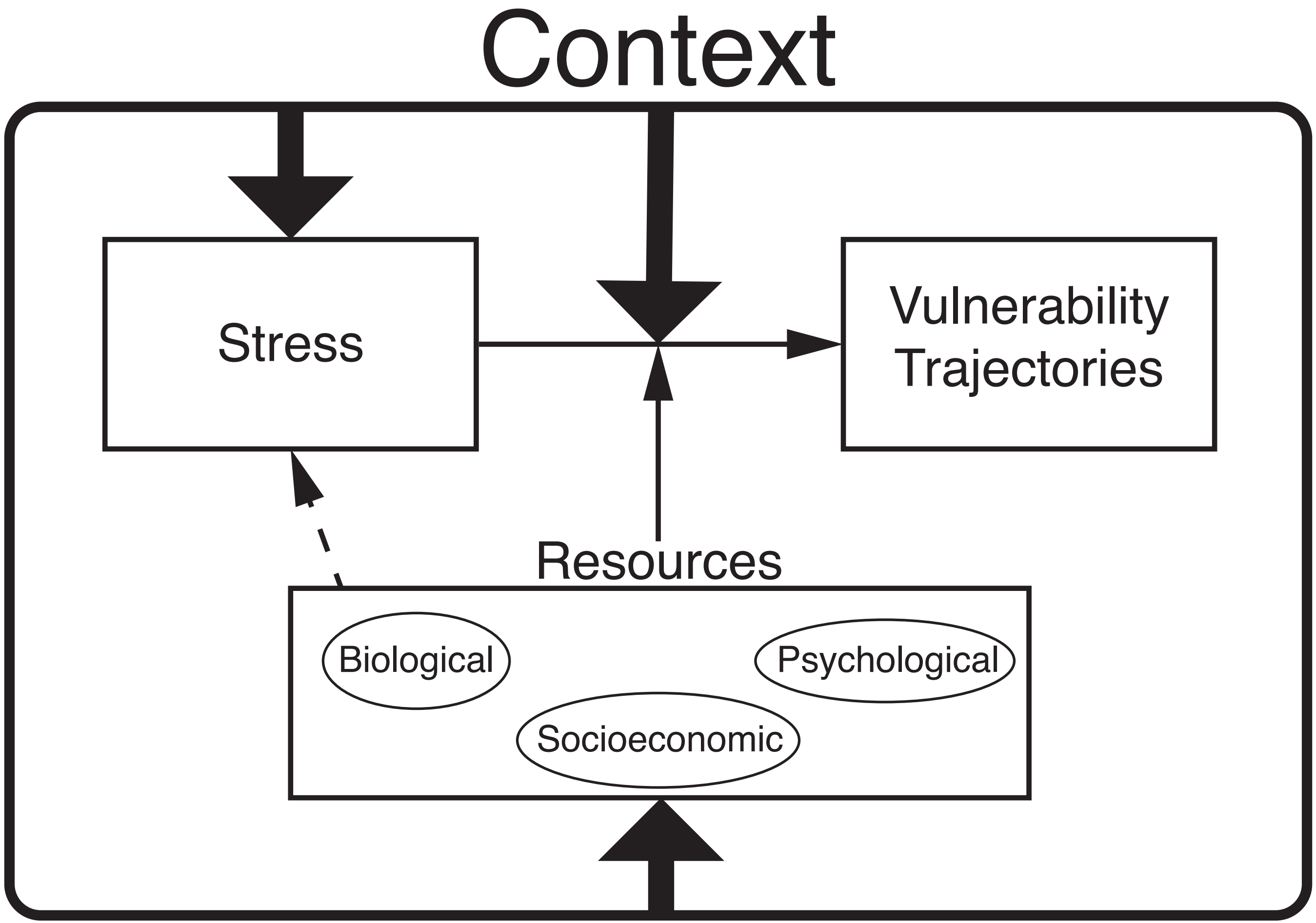

Figure 3.2 – Summary of Vulnerability as a Process (dashed lines are potential links)

available resources.

Resources are a crucial aspect in the vulnerability process, yet measuring them or analysing them is not straightforward. Firstly, resources can come from different domains, the three main types of resources being biological (individual), psychological and socioeconomic when the unit of analysis is the individual. Moreover, resources are multidimensional in themselves which makes capturing them difficult. Additionally, resources are not fixed in time. Individuals can accumulate or lose them, and certain resources, particularly reserves, may act with a delay, that is are not necessarily instantly available at any point in time.

The second aspect is context. The larger context plays a role in the allocation of resources, and can help by substituting resources or providing additional resources in times of need. However, it can also be a hindrance and limit access to resources or contribute to their unfair distribution. Context also plays a role in contributing to the increase or decrease of the chances of exposure to sources of stress.

These two elements subsequently play a role in establishing the trajectories individuals will take when exposed to a source of stress. These trajectories can vary between individuals and evolve over time. Vulnerability, therefore, is the process of dealing with sources of stress over time, attempting to minimize the harm that can be caused by stressors, and to recover from the negative consequences if they could not have been prevented.

If we apply this view of vulnerability to the specific case of the 2008 Financial Crisis, we have a punctual source of stress that could possibly be qualified as a life event. The particularity of the crisis, relative to other potential sources of stress, is that while socially produced, it was extremely wide-ranging and of a systemic nature. The worldwide and systemic nature of the crisis affected all sectors of the economy sparing almost no one in the short term. It can be seen as having affected everyone regardless of their resources and context. Thus, it can be argued that in terms of the risk of exposure to the crisis, there were no substantial differences between individuals.

Context nevertheless remains an important element in the relationship between sources of stress and vulnerability trajectories. For instance, in Section 2.2, we saw that the consequences of the crisis varied substantially between different countries. Countries whose economies relied more on investment in the United States for instance experienced more negative consequences. The same was true for countries whose economic growth prior to the crisis was linked to an expansion of the housing market such as Spain or Ireland. In the case of the labour market, measures such as the introduction of short-time work schemes, such as those implemented in Germany, limited the increase of unemployment. In the case of youth unemployment, countries with apprenticeship systems such as Austria saw less pronounced increases compared to countries without dual-education systems. In the case of health outcomes, the structure of public health systems also played a role in countries where health insurance is linked to employment such as Greece. As the crisis wore on, governmental responses to the crisis further changed the context especially in relation to budget cuts in the GIIPS countries which further shrunk the social safety and served to exacerbate the negative consequences of the crisis for individuals.

However, it is also important to further include the more long-term contextual changes especially the transformation of welfare regimes and the labour market. Full employment is no longer guaranteed (Esping-Andersen 1999, 25) and the manner in which countries choose to deal with this can influence the labour market consequences of the crisis. Liberal countries, such as the UK, principally attempted to reduce the problem through deregulation and pushing for more flexible labour markets. Consequently labour market regulation tends to be weaker in such countries than conservative countries, where stricter labour market regulations protect those in secure labour market positions to the detriment of individuals in less stable positions. In fact, Tridico (2013) finds that countries with less strict employment protection legislation saw greater increases in unemployment than countries with stricter protections.

As for resources, there are many possibilities in choosing resources that can affect the relationship between the crisis and subsequent trajectories. For instance, socioeconomic resources such as education, employment status, or income can be considered. In the case of labour markets, individuals with lower levels of education were more likely to experience unemployment. Moreover, younger individuals more often in less secure forms of employment were disproportionately affected by the crisis. As for the case of economic resources, although individuals and households at the top of the income and wealth distribution did see a slight decline in their situations, it was those at the bottom of the distribution that were the most severely affected in relation to poverty, deprivation, employment, or health.

Concerning trajectories of vulnerability, there is a wealth of different outcomes that can be investigated in relation to the crisis as its consequences were wide-ranging. We can look at employment trajectories, as will be the case in the applications in Chapters 6 and 7. Other possible consequences evoked in Section 2.2 that have been, or could be investigated, include trajectories of poverty and social exclusion, health, mortality, depression, or labour market entry.

3.4 Conclusion

This chapter outlines the vast literature that exists concerning the definition and conceptualization of vulnerability. Vulnerability is a concept that is thought to originate principally in the environmental sciences and that gained visibility by its use in disaster studies. However, somewhat in parallel, it is also a concept employed in the social sciences, most notably psychology, sociology, and gerontology, though its growing use coincides with the development of disaster studies as well as its increasing use in the context of climate change.

Despite the varying disciplines, time spans, and objects of study, there seems to be a somewhat of a minimal consensus on what vulnerability constitutes, or measures. Almost all definitions share one overarching commonality which is that vulnerability measures the degree to which an individual, household, community, or other object of study, is susceptible to experiencing harm. The manner in which harm is conceived can vary substantially, however, and depends not only on the discipline but also the context in which vulnerability is being studied.

What varies the most is the use of connected concepts such as risk or resilience. In the social sciences, risk is, in some cases (Chambers 1989), treated as a part of vulnerability or almost as a synonym for it (Beck 1992). Nevertheless, risk is more generally considered as conceptualizing the chances of experiencing a perturbation or source of stress that can subsequently lead to vulnerability.

Another closely related concept is resilience. There is some debate on whether resilience is a separate concept to vulnerability or an aspect of it. One view is that resilience can be viewed as the opposite of vulnerability; as the ability to resist or reduce harm. In certain cases, this is linked to the capacity to adapt or adaptability while in other cases this is considered to be a distinct attribute. Another view is that resilience can be considered as an attribute, or resource, which determines or modifies the degree of vulnerability (Turner II et al. 2003). In psychology and the social sciences, resilience is most often viewed in the first sense of the ability to avoid and prevent damage or negative consequences.

The framework proposed in Section 3.3 based on Spini et al. (2013) and Spini et al. (2017), which itself draws on the stress process model (Pearlin et al. 1981; Pearlin 1989), defines a broader view of vulnerability. Compared to other definitions of vulnerability, it more explicitly adds in the dimension of time as it outlines different stages in the vulnerability process: experiencing negative consequences, being unable to cope, and being unable to recover in set amount of time. This outlines the potential vulnerability processes an individual might follow when exposed to sources of stress.

The different possible trajectories of vulnerability are considered to be related to the different resources available. In the case of the study of individuals, which will be the main focus of the applications using this definition, these resources are expected to be one of three types: biological, psychological and socioeconomic. Resources are also multidimensional as each type of resource can be composed of multiple specific resources from each domain. These resources can vary over time, and their use and accumulation are linked to the more general context in which individuals are embedded in. Moreover, certain resources may not be available at every stage of an individual's life or are not used in all situations. This is the case of *reserves* (Cullati et al. 2018) which are resources accumulated over time whose use is deferred to some point in the future. Moreover, reserves are not intended to replace resources used in normal situations but supplement them in times where they are not enough to deal with situations individuals find themselves in.

Resources influence the trajectories of vulnerability individuals experience after exposure to a source of stress. Individuals with many resources, or who are adept at using the resources at their disposal, may never experience vulnerability even when exposed to stressors. Others still may limit the potential damage and never experience any negative consequences. However, others may not have the necessary resources and experience negative consequences or worse. Resources, however, cannot completely determine trajectories and differences remain in relation to individual agency. Resources can also potentially play a role in exposure to sources of stress as they can potentially be used to avoid a stressor entirely.

Finally, the exposure to stressors, the access to, and use of, resources, and trajectories are all embedded in the larger context. Contextual factors can play a role in aggravating or alleviating the consequences of sources of stress through multiple paths. Context can play a role in increasing or decreasing individual risk i.e. the chances of being exposed to a stressor. It can also influence the distribution, and use of resources, and it can also potentially influence the relationship between exposure to sources of stress and trajectories. Context, therefore plays a preponderant role in vulnerability as it influences all elements of the vulnerability process.

Modelling all of this can be a potentially daunting task as it requires, potentially, modelling differences in exposure to sources of stress, the interplay between stress and resources, trajectories all while taking into account the larger context and the time dimension. In Chapter 4, methods that can potentially be used to implement this framework will be explored and discussed.

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Chapter 4 Modelling Approaches

The challenges of defining and measuring vulnerability also extend to the choice of models used to analyse it. As vulnerability is considered to be a process, that means methods that work with longitudinal data are required. Additionally, we are not only interested in differences within individuals, but also in differences *between* individuals. This makes the use of fixed-effects panel models less appropriate than other longitudinal data models such as growth curve models as they only estimate *within*-individual change. Models that focus on within-individual change aim to understand change over time for a single individual. Models that focus on between-individual change serve to compare differences in change over time between different individuals. Latent variable models, as well as multilevel models, can be used to potentially analyse both within- and between-individual change. In this thesis, two main modelling approaches are employed: latent growth curve models and latent class models. However, these are very broad modelling techniques, with different frameworks that can be used to estimate the models. In fact, growth curve models as well as latent class models are now considered to be specific cases of models that belong to the general class of latent models which encompass a large number of models (see for instance Muthén (2002), Rabe-Hesketh et al. (2004), Skrondal and Rabe-Hesketh (2004), and Bartholomew et al. (2011)). A summary of the major types of latent variable models is shown in Table 4.1.

	Continuous Manifest Variables	Categorical Manifest Variables
Continuous Latent Variables	Factor analysis	Latent trait analysis
Categorical Latent Variables	Latent profile analysis	Latent class analysis

Table 4.1 – Major Types of Latent Variable Models
Adapted from Collins and Lanza (2010, 7) and Bartholomew et al. (2011, 11)

Structural equation modelling (SEM), of which factor analysis and growth curve modelling are special cases, considers that the underlying latent variables are continuous. Traditionally, the indicators, also called manifest variables, are also continuous though there have been developments which allow binary or ordinal manifest variables to be incorporated into the SEM framework. More recent efforts to develop estimation techniques in SEM are adopted from another special case of latent variable models: latent trait analysis or item-response theory. In this modelling framework, and particular case of latent variable modelling, the manifest variables are categorical while the latent variables are continuous. Latent class analysis (LCA) is another special case of latent variable modelling where the manifest variables are categorical as well as the latent variables. The final special case is latent profile analysis (LPA). In this framework, the latent variables are categorical and the manifest variables are continuous. The last two cases, LCA and LPA, are also part of a more general type of model termed mixture models (Oberski 2016).

In this chapter, the SEM framework, and more particularly the estimation of growth curve models within the framework, will be presented. Then, latent class models and their longitudinal extensions will be covered. In relation to the longitudinal extensions of latent class models, more particularly latent transition analysis, dynamic non-linear panel models will be discussed as an alternative estimation method for the structural part of the model.

4.1 (Latent) Growth Curve Models

Latent growth curve models originated as a method to describe changes in an outcome over time as a result of changes in characteristics between *and* within units of observation. Following the approach set out by Nesselroade and Baltes (1979) for the study of processes over time, growth curve models can be used to disentangle differences in change over time that are related to interindividual or *between*-individual differences from change related to intraindividual or *within*-individual change (Curran et al. 2010, 122–123; Grimm, Ram, and Estabrook 2017, 11). This contrasts with the more common approach to modelling longitudinal data in economics, and to some extent political science, which is the fixed effects approach that focuses on within-individual change in order to reduce bias related to omitted time-constant variables (Halaby 2004; Allison 2009; Andreß et al. 2013, 135).

Growth curve models are principally estimated within two frameworks: the structural equation modelling (SEM) framework, and the multilevel or mixed-effects framework. Most of the different specifications of growth models can be estimated in either framework and they often produce extremely similar or identical results in the case of continuous outcomes (McArdle and Hamagami 1996; Chih-Ping Chou et al. 1998; Curran 2003; Ghisletta and Lindenberger 2004; Grimm, Ram, and Estabrook 2017, 11). Where they differ is their relative advantages and disadvantages in estimating more complex models. For instance, the multilevel model framework is better for estimating complex piece-wise growth curve models where the transition from one growth process to another occurs at different points in time for different individuals.

The growth process, i.e. the form of the function describing change in the outcome as a function of time, needs to be specified in advance. The simplest form to express change in the dependent variable over time is as a linear function, in other words, the process is expressed in terms of an intercept and slope. It is also relatively straightforward to specify a quadratic, cubic, or higher-order functions of time. However, more complex specifications of time make interpretation more difficult and also require more data for the model to be estimated.

In this section, the general structural equation modelling framework (SEM) is presented, with a focus on developments integrating manifest categorical dependent variables. The implementation of growth curve models in the SEM framework is then further developed and the specification of different growth models within the framework is shown. Finally, some extensions to standard growth curve models are considered before concluding.

4.1.1 The Structural Equation Modelling Framework

Structural equation modelling (SEM) is a general term for a framework in which multiple statistical analyses can be implemented such as path analysis, factor analysis, time-series, etc. Recent developments such as those by Skrondal and Rabe-Hesketh (2004) or Bartholomew et al. (2011) propose an even more general framework which incorporates SEM, as well as many other latent variable models which can be extended to incorporate longitudinal data. The main motivation behind the development of SEM was to better combine theoretical frameworks and the methods available to test them. This was discussed by Goldberger (1973) who presented issues related to the estimation of causal models in the presence of unobservable, or latent variables, in addition to estimating equations simultaneously. The modern development and use of SEM is principally due to the implementation and use of confirmatory factor analysis with latent variables in combination with path analysis or simultaneous equation modelling (Kaplan 2009, 5).

LISREL, (Jöreskog 1973; McArdle and Kadlec 2013, 296; McArdle and Nesselroade 2014, 43) was one of the first implementations combining multivariate regression with the concept of common factors. It is a very general framework that allows testing, potentially very complex, hypotheses by explicitly specifying and estimating multiple relationships in a single model simultaneously. The LISREL implementation of SEM (Jöreskog 1973) defines all relationships between manifest and latent variables in a model using eight matrices (McArdle and Nesselroade 2014, 44).

These matrices define the relationship between manifest indicators and latent variables for both the independent and dependent variables, the relationships between the independent, latent $\boldsymbol{\xi}$ or manifest $\boldsymbol{x}$, variables, the relationships between the dependent, latent $\boldsymbol{\eta}$ or manifest $\boldsymbol{y}$, variables (if there are more than one), and the relationships between the independent and dependent latent variables. The general equation which establishes the structure of the relationship between latent variables is given by (Muthén 1984; Bollen 1989, 319; Rabe-Hesketh et al. 2004):

$$\boldsymbol{\eta} = \mathbf{B}\boldsymbol{\eta} + \boldsymbol{\Gamma}\boldsymbol{\xi} + \boldsymbol{\zeta} \tag{4.1}$$

where $\boldsymbol{B}$ is the coefficient matrix, or loadings, for the dependent latent variables $\boldsymbol{\eta}$, $\boldsymbol{\Gamma}$ is the coefficient matrix for the independent latent variables and ζ contains the errors.

The measurement model defining the independent latent variables is:

$$\boldsymbol{x} = \boldsymbol{\Lambda}_{\boldsymbol{x}}\boldsymbol{\xi} + \boldsymbol{\delta} \tag{4.2}$$

where $\boldsymbol{\Lambda}_{\boldsymbol{x}}$ is the coefficient matrix, or loadings, relating the latent variable $\boldsymbol{\xi}$ to the manifest variable $\boldsymbol{x}$ and δ contains the errors. The measurement model defining the dependent latent variables is:

$$\boldsymbol{y} = \boldsymbol{\Lambda}_{\boldsymbol{y}}\boldsymbol{\eta} + \boldsymbol{\epsilon} \tag{4.3}$$

where $\boldsymbol{\Lambda_y}$ is the coefficient matrix, or loadings, relating the latent variable $\boldsymbol{\eta}$ to the manifest variable $\boldsymbol{y}$ and $\boldsymbol{\epsilon}$ contains the errors.

Equations (4.2) and (4.3) are the measurement models which specify the latent variables in relation to the manifest variables, or indicators, which correspond to the variables that are observed or contained in the data. These equations also correspond to the equations for a confirmatory factor analysis (CFA) model.

The most common manner to estimate a model within the SEM framework, assuming that the errors $\boldsymbol{\zeta}$, $\boldsymbol{\delta}$ and $\boldsymbol{\epsilon}$ are normally distributed, is using maximum likelihood (Jöreskog 1973; Bollen 1989, 107) to minimize the following log-likelihood:

$$F_{\mathrm{ML}} = \log|\boldsymbol{\Sigma}(\theta)| + \mathrm{tr}(\mathbf{S}\boldsymbol{\Sigma}^{-1}(\theta)) - \log|\mathbf{S}| - (p+q) \tag{4.4}$$

where θ is all the parameters that need to be estimated: $\boldsymbol{\eta}$, $\boldsymbol{B}$, $\boldsymbol{\Gamma}$, $\boldsymbol{\xi}$, $\boldsymbol{\Lambda}_x$, $\boldsymbol{\Lambda}_y$, as well as the variances and covariances of the errors $\boldsymbol{\zeta}$, $\boldsymbol{\delta}$ and $\boldsymbol{\epsilon}$. $\boldsymbol{\Sigma}(\theta)$ is the implied covariance matrix of the structural equation model i.e. the variance-covariance matrix of the manifest variables, p is the number of manifest, or observed, dependent (y) variables, q is the number of manifest, or observed, independent (x) variables, and $\mathbf{S}$ is the sample covariance matrix i.e. the variances and covariances of the manifest variables. $\mathbf{S}$ is defined as:

$$\begin{bmatrix} \mathrm{var}(y) & \mathrm{covar}(x,y) \\ \mathrm{covar}(y,x) & \mathrm{var}(x) \end{bmatrix} \tag{4.5}$$

The implied covariance matrix $\Sigma(\theta)$ is defined as (Jöreskog 1973, 107; Bollen 1989, 325):

$$\boldsymbol{\Sigma}(\theta) = \begin{bmatrix} \boldsymbol{\Sigma}_{yy}(\theta) & \boldsymbol{\Sigma}_{yx}(\theta) \\ \boldsymbol{\Sigma}_{xy}(\theta) & \boldsymbol{\Sigma}_{xx}(\theta) \end{bmatrix} \tag{4.6}$$

The four submatrices, $\Sigma_{yy}(\theta)$, $\Sigma_{xx}(\theta)$, $\Sigma_{yx}(\theta)$, and $\Sigma_{xy}(\theta)$ are the covariance matrices of the manifest y variables, the covariance matrix for the manifest x variables, and the covariance matrices between the x and y variables respectively. Following Bollen's (1989, 324–325) notation and Equations (4.1) and (4.3) the covariance matrix $\boldsymbol{\Sigma}_{yy}(\theta)$ is:

$$\boldsymbol{\Sigma}_{yy}(\theta) = \boldsymbol{\Lambda}_y(\mathbf{I}-\mathbf{B})^{-1}(\boldsymbol{\Gamma}\boldsymbol{\Phi}\boldsymbol{\Gamma}' + \boldsymbol{\Psi})\left[(\mathbf{I}-\mathbf{B})^{-1}\right]'\boldsymbol{\Lambda}_y' + \boldsymbol{\Theta}_\epsilon \tag{4.7}$$

where $\boldsymbol{\Lambda}_y$ is the matrix of loadings (coefficient matrix) for the y observed variables, $\mathbf{I}$ is the identity matrix, and $\boldsymbol{\Theta}_\epsilon$ is the covariance matrix for the measurement error of the endogenous latent variables. The other matrices – $\mathbf{B}$, $\boldsymbol{\Gamma}$, $\boldsymbol{\Phi}$, and $\boldsymbol{\Psi}$ – are described in Table 4.2.

$\mathbf{B}$	The coefficient matrix for the endogenous latent variables
$\boldsymbol{\Gamma}$	The coefficient matrix for the exogenous latent variables
$\boldsymbol{\Phi}$	The covariance matrix of the latent exogenous variables (ξ)
$\boldsymbol{\Psi}$	The covariance matrix of the latent errors (ζ)

Table 4.2 – SEM Matrices

The covariance matrix $\boldsymbol{\Sigma}_{xx}(\theta)$ can be expressed as:

$$\boldsymbol{\Sigma}_{xx}(\theta) = \boldsymbol{\Lambda}_x\boldsymbol{\Phi}\boldsymbol{\Lambda}_x' + \boldsymbol{\Theta}_\delta \tag{4.8}$$

where $\mathbf{\Lambda}_x$ is the matrix of factor loadings for the observed independent, or x, variables, $\mathbf{\Phi}$ is the covariance matrix of the latent exogenous variables, and $\mathbf{\Theta}_\delta$ is the covariance matrix for the errors of the measurement model of the exogenous latent variables.

The covariance matrix $\mathbf{\Sigma}_{yx}(\theta)$ is defined as:

$$\mathbf{\Sigma}_{yx}(\theta) = \mathbf{\Lambda}_y(\mathbf{I} - \mathbf{B})^{-1}\mathbf{\Gamma}\mathbf{\Phi}\mathbf{\Lambda}'_x \tag{4.9}$$

where $\mathbf{\Lambda}_y$ is the matrix of factor loadings for the dependent latent variables, $\mathbf{\Lambda}_x$ is the matrix of factor loadings for the independent latent variables, and $\mathbf{I}$ is the identity matrix. The other matrices, $\mathbf{B}$, $\mathbf{\Gamma}$, and $\mathbf{\Phi}$, are described in Table 4.2. Finally, the covariance matrix $\mathbf{\Sigma}_{xy}(\theta)$ is $\mathbf{\Sigma}_{yx}(\theta)'$, the transpose.

Confirmatory factor analysis, and by extension growth curve models as will be shown in Section 4.1.2, are a special limited case of the general latent variable model. In the case of a confirmatory factor analysis model, the implied covariance matrix $\Sigma(\theta)$ reduces to only the $\Sigma_{xx}(\theta)$ covariance matrix in Equation (4.8).

The maximum likelihood estimator defined in Equation (4.4) can be used to estimate almost any structural equation model as long as the indicators measuring the latent variables are continuous. This estimator, however, is inconsistent when the manifest variables are non-normally distributed such as in the case of binary indicators (Muthén 1979, 1984; Gibbons and Bock 1987; Muthén 1996).

Missing Data

Another particularity of the estimator in Equation (4.4) is that it doesn't actually require the raw individual-level data, but rather summaries of the individual cases i.e. the covariance matrices.

This can be considered as an advantage in the case of missing data as pairwise correlations can be used. However, the use of pairwise correlations increases the risk of problems with model estimation due to non-invertible matrices (Wothke 1993). This is further compounded in the longitudinal case where attrition and unbalanced data are especially common for panel data surveys. Moreover, most software designed to estimate SEM models uses longitudinal data in the *wide* format rather than the *long* format (see Tables 4.3 and 4.4). Using list-wise deletion and even pairwise deletion can potentially lead to a substantial reduction in the data available to estimate the model.

ID	Sex	Employed_1	Employed_2	Employed_3
i-01	Female	Yes	Yes	Yes
i-02	Male	Yes	No	Yes
⋮	⋮	⋮	⋮	⋮
i-20	Female	Yes	———	No

Table 4.3 – Example of Data in Wide Format

An early approach to dealing with missing data using maximum likelihood estimation in structural equations models was proposed by Allison (1987) and Muthén

ID	Time	Sex	Employed
i-01	1	Female	Yes
i-01	2	Female	Yes
i-01	3	Female	Yes
i-02	1	Male	Yes
i-02	2	Male	No
i-02	3	Male	Yes
⋮	⋮	⋮	⋮
i-20	1	Female	Yes
i-20	2	Female	———
i-20	3	Female	No

Table 4.4 – Example of Data in Long Format

et al. (1987). In this approach, the sample is subdivided into groups with identical missing data patterns. Then, a likelihood is calculated for each group and subsequently pooled and the combined likelihood is then maximized (Enders 2001). Both approaches, however, are impractical when there is a large number of patterns of missing data or when certain patterns only appear a few times in the data (Allison 2003). Arbuckle (1996) proposed a more general "full-information" maximum likelihood estimator which can take into account an arbitrary number of missing data patterns. This estimator is derived from one proposed by Finkbeiner (1979) for the case of confirmatory factor analysis and Arbuckle extends it to the case of general SEM.

The estimator proposed by Arbuckle (1996) uses the complete data of each case, rather than of groups, to create a combined likelihood function for all cases and the likelihood is subsequently maximized. For an individual i, the individual contribution to the log-likelihood, assuming normality, is defined as:

$$\log L_i = K_i - \frac{1}{2}\log|\boldsymbol{\Sigma}_i| - \frac{1}{2}(\mathbf{x}_i - \boldsymbol{\mu}_i)'\boldsymbol{\Sigma}_i^{-1}(\mathbf{x}_i - \boldsymbol{\mu}_i) \tag{4.10}$$

The K_i term is constant and depends on the number of complete observations for a case i. $\boldsymbol{\Sigma}_i$ is the covariance matrix containing the covariances for all the variables for which there is complete data for case i. $\mathbf{x}_i$ is the vector containing the complete data for case i and $\boldsymbol{\mu}_i$ is the vector containing the sample means, i.e. calculated directly from the data, of the variables for which there is complete information for case i. The combined log-likelihood for the complete model simply becomes a sum of each of the individual log-likelihoods:

$$\log L(\boldsymbol{\mu}, \boldsymbol{\Sigma}) = \sum_{i=1}^{N} \log L_i \tag{4.11}$$

Both the mean, i.e. the $\boldsymbol{\mu}$ vector, and the covariance matrix, i.e. the $\boldsymbol{\Sigma}$, can be expressed in terms of a specific parameter vector $\boldsymbol{\theta}$. The estimates of the parameters in $\boldsymbol{\theta}$ can be obtained by minimizing the following function (Arbuckle

1996, 248; Bollen and Curran 2006, 64):

$$\begin{aligned} C(\boldsymbol{\theta}) &= -2\log L(\boldsymbol{\mu}(\boldsymbol{\theta}), \boldsymbol{\Sigma}(\boldsymbol{\theta})) + 2\sum_{i=1}^{N} K_i \\ &= \sum_{i=1}^{N} \log|\boldsymbol{\Sigma}_i(\boldsymbol{\theta})| + \sum_{i=1}^{N} (\boldsymbol{x}_i - \boldsymbol{\mu}_i(\boldsymbol{\theta}))' \boldsymbol{\Sigma}_i^{-1}(\boldsymbol{\theta})(\boldsymbol{x}_i - \boldsymbol{\mu}_i(\boldsymbol{\theta})) \end{aligned} \tag{4.12}$$

Studies on the full-information maximum likelihood estimator also show that it is asymptotically equivalent to multiple imputation when there is missing data while being a more efficient estimator (Enders and Bandalos 2001; Allison 2003). Both full-information maximum likelihood and multiple imputation are suitable for dealing with missing data that is missing at random, or completely at random.

Binary and Ordinal Data

So far the estimators that have been presented here apply to the case where the manifest variables, or indicators, measuring the factors are continuous. However, further developments have led to the implementation of techniques that allow binary or ordinal dependent variables, to be modelled directly. One of the most common estimation techniques used to incorporate noncontinuous dependent variables in the SEM framework is the weighted least squares estimator (Kaplan 2009, 15). This estimation technique is also employed in the standard regression frameworks to estimate models with binary or ordinal dependent variables. In most cases, weighted least squares provides is equivalent to maximum likelihood estimation when estimating a model with a binary or ordinal dependent variable (Bradley 1973) and is less computationally difficult to implement than a direct maximum likelihood estimator which requires numerical integration.

A concrete example of this estimator is the one implemented in Mplus which is the “WLSMV”, weighted least square mean and variance adjusted, estimator and which estimates a random-effects probit model. It is an improved version of the estimator introduced in Muthén (1984) which was developed as a computationally feasible estimator based on a maximum likelihood estimator for SEM models with binary or ordinal indicators (Muthén 1979). Starting from a general structural equation model with latent variables as defined in Equation (4.1), Muthén expresses the noncontinuous indicators as latent variables using a threshold formulation. The hypothesis is that there is an underlying continuous variable y^* which is measured by binary or ordinal indicators:

$$\boldsymbol{y}^* = \boldsymbol{v}_y + \boldsymbol{\Lambda}_y \boldsymbol{\eta} + \boldsymbol{\epsilon} \tag{4.13}$$

This expression is almost the same as that in Equation (4.3) which specifies the measurement model for the y variables. It, however, includes a new term $\boldsymbol{v}_y$ which is an intercept. In the case of a binary dependent variable this expression can be simplified by setting the intercept vector to 0.

The relationship between the underlying latent variable y^* and the observed binary or ordinal indicators can be expressed in terms of thresholds:

$$\begin{cases} y = 1 \text{ if } y^* > \tau_1 \\ y = 0 \text{ if } y^* \leq \tau_1 \end{cases} \tag{4.14}$$

The observed discrete values of the manifest variables are considered to be imperfect measurements of an underlying continuous latent variable. Consequently, we observe a value of 1 above a certain threshold τ in the distribution of the underlying continuous variable otherwise we observe 0. This formulation can easily be extended to ordinal dependent variables with each subsequent observed value corresponding to a higher threshold:

$$\begin{cases} y = (n-1) \text{ if } \tau_{(n-1)} < y^* \leq \tau_n \\ \vdots \\ y = 2 \text{ if } \tau_2 < y^* \leq \tau_3 \\ y = 1 \text{ if } \tau_1 < y^* \leq \tau_2 \\ y = 0 \text{ if } y^* \leq \tau_1 \end{cases} \tag{4.15}$$

To estimate the thresholds, it is assumed that the underlying latent variable is normally distributed with a mean of 0 and a variance of 1. Fixing the mean and variance of the underlying distribution is necessary to ensure that the model estimating the thresholds can be identified. The thresholds then correspond to the cumulative sample proportion of cases in a specific category and are calculated as follows:

$$\tau_j = \Phi^{-1}\left(\sum_{c=1}^{j} \pi_c\right)$$

with Φ^{-1} being the inverse of the cumulative normal distribution and π_c is the proportion of respondents in a category c of y in the data. Once the thresholds are determined, then polychoric correlations can be estimated using maximum likelihood and the estimator proposed by Olsson (1979). Once the thresholds and correlations are calculated, they can then be used to calculate the necessary components of the covariances σ and a weighted least squares estimator defined as the values that minimize (Muthén 1983, 51; 1984, 119; Bollen 1989, 443; Muthén 1996, 44):

$$F = (\boldsymbol{s} - \boldsymbol{\sigma}')\boldsymbol{W}^{-1}(\boldsymbol{s} - \boldsymbol{\sigma}) \tag{4.16}$$

F is the fit function, $\boldsymbol{s}$ is a vector containing the sample covariances and, depending on software, the sample-estimated thresholds. $\boldsymbol{\sigma}$ is a vector which is the implied covariance matrix stacked in vector form, containing the same model-implied parameters, covariances and, depending on software, thresholds, as $\boldsymbol{s}$. $\boldsymbol{W}$ is the weight matrix which corresponds to the asymptotic covariance matrix of the sample-estimated covariances between the latent variables (Bollen and Curran 2006; Finney and DiStefano 2013). The approach proposed by Muthén (1983, 1984), Muthén and Satorra (1995), and Muthén (1996) estimates Equation (4.16) in three stages. The first and second stages estimate the $\boldsymbol{\sigma}$ vector. The final stage is the calculation of $\boldsymbol{W}$ and the estimation of the fit function in Equation (4.16).

The standard weighted least squares estimator is biased unless the sample size is large. Additionally, the inversion of the full weight matrix can be computationally intensive. A more robust estimator, diagonal weighted least squares, was implemented by Muthén et al. (1997) and the estimator in Equation (4.16) now only uses the diagonal of the asymptotic covariance matrix – $\mathrm{diag}\,(\boldsymbol{W})$ (Bollen and Curran 2006; Finney and DiStefano 2013). To avoid the underestimation of standard errors, a robust estimator of the asymptotic covariance matrix is obtained using the diagonal weight matrix, and the non-inverted asymptotic covariance matrix as defined in Muthén et al. (1997, 4) and Muthén (1998-2004, 19). This estimator was principally developed as at the time, pure maximum likelihood approaches to growth models with categorical data were computationally difficult to estimate.

Another option for estimating structural equation models with binary and ordinal dependent variables which has become viable is the use of full-information maximum likelihood estimators. This provides the same advantage as in the case of continuous indicator variables as all available non-missing information can be included in the estimation of a model. The major downside is that the model estimation can be very computationally intensive especially with many latent variables. While structural equation models with only continuous indicators have a closed-form solution for obtaining estimates, this is not the case for noncontinuous indicators.

The models and methods used for estimating models with ordinal and binary dependent variables with full-information maximum likelihood in the SEM framework are derived from item-response theory and latent trait models (Bock and Aitkin 1981; Bock et al. 1988; Moustaki 2007; Kamata and Bauer 2008). A general latent variable model can be estimated using marginal likelihood estimators where the latent variables have been marginalized (Bock et al. 1988; Moustaki and Knott 2000, 395; Rabe-Hesketh et al. 2004; Hedeker and Gibbons 2006, 163–164; Bartholomew et al. 2011, 7; Fitzmaurice et al. 2011, 410; Cagnone and Monari 2013):

$$f(\boldsymbol{y}) = \int_{R_q} g(\boldsymbol{y}|\boldsymbol{z})h(\boldsymbol{z})d\boldsymbol{z} \tag{4.17}$$

Here $\boldsymbol{y}$ is a vector of length p containing the p observed binary or ordinal variables, $\boldsymbol{z}$ is the vector containing the q latent variables. The first function g specifies the conditional probability of observing our outcome(s) in $\boldsymbol{y}$ conditional on the latent variables in $\boldsymbol{z}$. This function g corresponds to the measurement model of the latent variables and is analogous to Equations (4.2) and (4.3) in the continuous case. The function h specifies the relationships between the latent variables and thus corresponds to the structural part of the overall model which is analogous to Equation (4.1) in the continuous case. $\boldsymbol{z}$ is assumed to follow a multivariate normal distribution. The dimension, R_q, of the integral increases according to the number, q, of latent variables.

It is assumed that the observed variables are independent conditional on the latent variable – the local independence assumption – and therefore the measurement model $g(\boldsymbol{y}|\boldsymbol{z})$ can be expressed as

$$\prod_{i=1}^{p} g_i(y_i|z)$$

This means that a different function g can be specified for each manifest variable which allows for specifying a different link function for each of the p indicators y_i such as the logit, probit, or poisson links as well as the normal distribution. Substituting this expression into Equation (4.17) we get:

$$f(\boldsymbol{y}) = \int_{R_q} \left[\prod_{i=1}^{p} g_i(y_i|z) \right] h(\boldsymbol{z}) d\boldsymbol{z} \tag{4.18}$$

The log-likelihood for a sample m of size n is given by:

$$L = \sum_{m=1}^{n} \log f(\boldsymbol{y}) = \sum_{m=1}^{n} \log \int_{R_q} \left[\prod_{i=1}^{p} g_i(y_i|z) \right] h(\boldsymbol{z}) d\boldsymbol{z} \tag{4.19}$$

To evaluate the integral, numerical approximations are calculated using Gauss-Hermite quadrature, or more recently adaptive quadrature (Skrondal and Rabe-Hesketh 2004; Rabe-Hesketh et al. 2004; Cagnone and Monari 2013; Bryant and Jöreskog 2016). The likelihood is maximized, using algorithms such as the expectation maximization (EM) algorithm (Dempster et al. 1977), Newton-Raphson, Fisher scoring, or a combination thereof (Skrondal and Rabe-Hesketh 2004; Bartholomew et al. 2011; Muthén and Muthén, 1998–2015, 9).

4.1.2 Specifying Growth Curve Models in the SEM Framework

One of the most common longitudinal models in the SEM framework is the (latent) growth curve model. Meredith and Tisak (1990) showed that it is possible to reformulate a random-coefficient growth curve model as a specific case of a structural equation model. They express a growth model as:

$$\mathbf{x} = \Gamma w + e \tag{4.20}$$

which, barring the different notation, corresponds to a measurement model as expressed in Equation (4.2) or (4.3). The latent variables which describe change over time, w, are measured by repeated observations of a manifest variable, x, over time with Γ being the coefficient matrix (factor loadings) and e the error. Thus, a latent growth curve model, with no covariates, is simply a special case of a confirmatory factor analysis model.

Growth curve models aim to model longitudinal processes, especially change in an outcome over time, and explain change *within* individuals over time but also difference *between* individuals in change over time (Halaby 2003; Grimm, Ram, and Estabrook 2017). In the simplest case of modelling change over time in a dependent variable, there are two latent factors that need to be estimated: one for the intercept, and one for the slope. The path diagram for this model is presented in Figure 4.1.

In the rest of this section, the equations will follow the notation in Bollen and Curran (2006) both for the structural equation matrix notation, and the multilevel or mixed-effects notation. At the observation level, a growth curve model without any covariates for a single individual can be expressed as follows:

$$y_{it} = \alpha_i + \lambda_t \beta_i + \epsilon_{it} \tag{4.21}$$

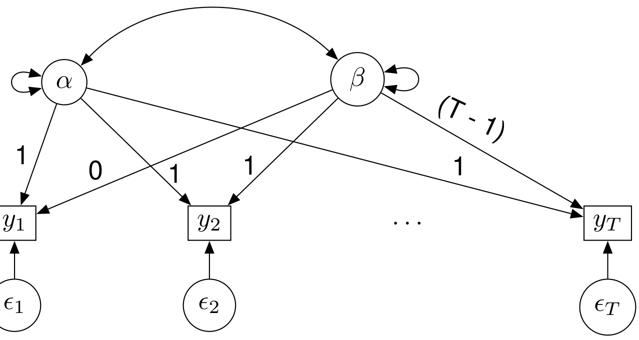

Figure 4.1 – Simple Linear Growth Curve Model

In the multilevel framework, λ_t is a variable, which corresponds to the time of measurement. In the SEM framework, it is a predefined factor loading.

This equation shows that with a growth curve model, we try to explain the level of a dependent variable for an individual i at time t by two coefficients: α_i and β_i. These coefficients are specific to each individual. α_i is time-constant while the effect ofβ_i varies over time according to λ_t. ϵ_{it} is the idiosyncratic error term. This equation illustrates a *linear* growth curve model as it is the same form as a linear equation. α_i is the individual-specific intercept while β_i is the individual-specific slope. The α_i and β_i coefficients can further be decomposed into an individual-specific component and the mean of the coefficients for all cases. This gives us two additional equations:

$$\alpha_i = \mu_\alpha + \zeta_{\alpha i} \tag{4.22}$$

$$\beta_i = \mu_\beta + \zeta_{\beta i} \tag{4.23}$$

Equations 4.22 and 4.23 express the coefficients of the ith growth trajectory as the mean value of the coefficients for all cases plus an individual-specific deviation. When we combine Equations (4.21) (4.22) and (4.23), we can express the full model as:

$$y_{it} = (\mu_\alpha + \zeta_{\alpha i}) + \lambda_t (\mu_\beta + \zeta_{\beta i}) + \epsilon_{it} \tag{4.24}$$

This notation is traditionally more commonly used in the multilevel or mixed effects modelling framework.

In the case of growth curve models in the SEM framework, a matrix notation is more commonly used. A growth curve model with no covariates is expressed as:

$$\mathbf{y} = \boldsymbol{\Lambda}\boldsymbol{\eta} + \boldsymbol{\epsilon} \tag{4.25}$$

which corresponds to the formulation proposed by Meredith and Tisak (1990) in Equation (4.20) and is also referred to as the “all-y” LISREL notation (Newsom 2015, 383–389). $\mathbf{y}$ is a vector containing all the observations of an individual i for the T time periods. The $\boldsymbol{\Lambda}$ matrix contains the time scores i.e. the time points of each measurement. The $\boldsymbol{\eta}$ vector contains our growth coefficients α_i and β_i in Equation 4.21. The $\boldsymbol{\eta}$ vector can be further decomposed into two vectors containing the mean trajectory coefficients and the individual-specific deviation from the mean as in Equations 4.22 and 4.23. Thus we have:

$$\boldsymbol{\eta} = \boldsymbol{\mu_\eta} + \boldsymbol{\zeta} \tag{4.26}$$

and Equation 4.25 becomes:

$$\mathbf{y} = \boldsymbol{\Lambda}\left(\boldsymbol{\mu_\eta} + \boldsymbol{\zeta}\right) + \boldsymbol{\epsilon} \tag{4.27}$$

We can further expand this equation and show the vectors and matrices more explicitly:

$$\begin{pmatrix} y_{i1} \\ y_{i2} \\ \vdots \\ y_{iT} \end{pmatrix} = \begin{pmatrix} 1 & 0 \\ 1 & 1 \\ \vdots & \vdots \\ 1 & T-1 \end{pmatrix} \left[\begin{pmatrix} \mu_\alpha \\ \mu_\beta \end{pmatrix} + \begin{pmatrix} \zeta_{\alpha i} \\ \zeta_{\beta i} \end{pmatrix} \right] + \begin{pmatrix} \epsilon_{i1} \\ \epsilon_{i2} \\ \vdots \\ \epsilon_{iT} \end{pmatrix} \tag{4.28}$$

If we relate this to our path diagram in Figure 4.1, our $\mathbf{y}$ vector corresponds to the squares containing the ys. The $\boldsymbol{\Lambda}$ matrix corresponds to the factor loadings. The first column of the matrix contains the loadings for the intercept factor α while the second column of $\boldsymbol{\Lambda}$ corresponds to the loadings for the slope factor β. The means of our two latent factors α and β are μ_α and μ_β respectively. The individual-specific deviations from the mean are not included directly. Rather, they are included via the variance of the slope and intercept factors which are the parameters of the growth curve.

If we relate this matrix expression to Equation (4.24), we find the same terms. The main difference is how time is expressed. In Equation (4.21) the time-constant aspect of the first parameter of the growth curve – the time-constant α_i is not explicit unlike the structural equation formulation. A more explicit equivalent is:

$$y_{it} = \lambda_t^0\left(\mu_\alpha + \zeta_{\alpha i}\right) + \lambda_t^1\left(\mu_\beta + \zeta_{\beta i}\right) + \epsilon_{it} \tag{4.29}$$

This shows that each *column* of the Λ matrix which we use to define the factor loadings corresponds to time to the power of the column position. Thus, in the case of a “no-growth” model, or one where we don’t hypothesize any change over time, the Λ matrix would have only a single column. In the case where we suppose simple linear change, as in our current example, we have two columns.

The variances of the slope and intercept factors, which are *continuous* latent factors, allow us to take into account the *between*-individual variation in growth processes over time. The means of the latent factors, in the case of a continuous outcome which is considered to be normally distributed, correspond to the *population* mean and describe the average *within*-individual change over time. In addition the individual variances for each factor, the shape factors – the intercept and slope – are allowed to covary. This means that the latent factors are not considered to be independent. More concretely, this allows for a relationship between the time-constant component and time-varying component of the trajectory to be related, that is the level of change over time is linked to the initial level.

The interpretation of the mean of the slope factor in a linear model is relatively straightforward. It quantifies the result of a one-unit change in the time metric on the level of the dependent variable. The interpretation of the mean of the intercept, or time-constant, factor can be more nuanced. It gives the mean of the level of the dependent variable when the time score is zero. However, a time score of zero doesn't necessarily correspond to the initial level of the dependent variable. It is possible to centre the time variable differently. In the case of the example model in Figure 4.1, it is possible to centre time at the second measurement as illustrated in Figure 4.2.

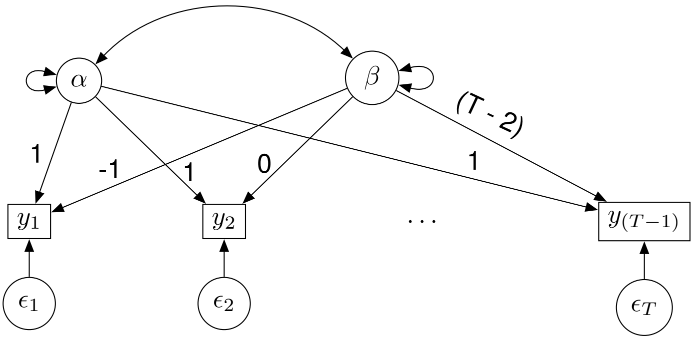

Figure 4.2 – Simple Linear Growth Curve Model
Time centred at measurement occasion 2

This changes the interpretation of the mean of the intercept factor which becomes the overall level of the dependent variable at measurement occasion two rather than the overall level of the initial measurement as in Figure 4.1. It also changes the interpretation of the covariance. Instead of it being the relationship between change over time and the initial level, it corresponds to the covariance between change over time and the level of the dependent variable at the second measurement.

In addition to changing the centring, change over time can be modelled more flexibly. We can have a quadratic growth curve model which gives the following path diagram:

We can see that compared to Figure 4.1 the diagram in Figure 4.3 introduces a third latent variable, β_2 which is the quadratic component of the growth curve model and the factor loadings are simply the factor loadings of the linear component squared. The quadratic factor β_2 also has its own mean and variance. There are also now three covariances: the one between the intercept factor and the slope factor as in a linear model, an additional one between the quadratic factor and the intercept factor, and another between the linear factor and the quadratic factor.

Using the SEM matrix notation this diagram can be expressed as:

$$\begin{pmatrix} y_{i1} \\ y_{i2} \\ \vdots \\ y_{iT} \end{pmatrix} = \begin{pmatrix} 1 & 0 & 0 \\ 1 & 1 & 1 \\ \vdots & \vdots & \vdots \\ 1 & T-1 & (T-1)^2 \end{pmatrix} \left[\begin{pmatrix} \mu_\alpha \\ \mu_{\beta_1} \\ \mu_{\beta_2} \end{pmatrix} + \begin{pmatrix} \zeta_{\alpha i} \\ \zeta_{\beta_1 i} \\ \zeta_{\beta_2 i} \end{pmatrix} \right] + \begin{pmatrix} \epsilon_{i1} \\ \epsilon_{i2} \\ \vdots \\ \epsilon_{iT} \end{pmatrix} \tag{4.30}$$

In this equation we now have *three* latent variables as evidences by the three

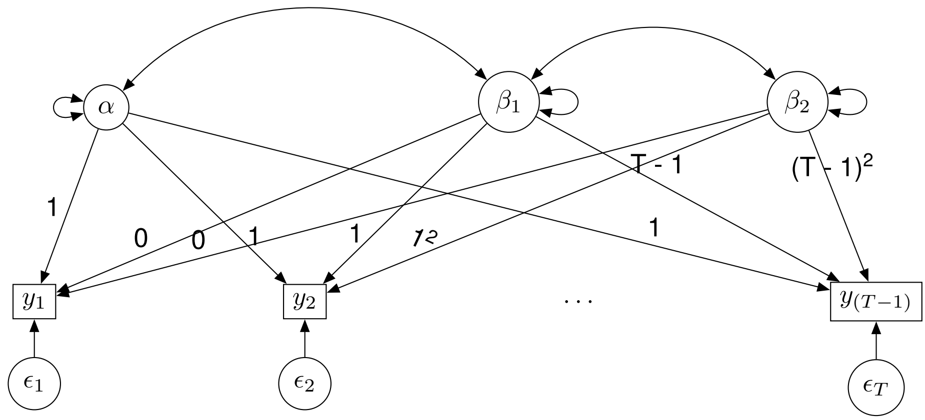

Figure 4.3 – Quadratic Growth Curve Model

means μ_α, μ_{β_1}, and μ_{β_2}, one for the time-constant component of the curve, one for the linear component, and one for the quadratic component, and their respective individual-specific deviations.

If we formulate this model in terms of the multilevel modelling notation, we have the following level-1 equation:

$$y_{it} = \alpha_i + \lambda_t \beta_{1i} + \lambda_t^2 \beta_{2i} + \epsilon_{it} \tag{4.31}$$

and the following three level-2 equations:

$$\alpha_i = \mu_\alpha + \zeta_{\alpha i} \tag{4.32}$$

$$\beta_{1i} = \mu_{\beta_1} + \zeta_{\beta_1 i} \tag{4.33}$$

$$\beta_{2i} = \mu_{\beta_2} + \zeta_{\beta_2 i} \tag{4.34}$$

which gives the following combined equation:

$$\begin{aligned} y_{it} =& (\mu_\alpha + \zeta_{\alpha i}) + \lambda_t(\mu_{\beta_1} + \zeta_{\beta_1 i}) + \lambda_t^2(\mu_{\beta_2} + \zeta_{\beta_2 i}) + \epsilon_{it} \\ =& (\mu_\alpha + \lambda_t \mu_{\beta_1} + \lambda_t^2 \mu_{\beta_2}) + (\zeta_{\alpha i} + \lambda_t \zeta_{\beta_1 i} + \lambda_t^2 \zeta_{\beta_2 i}) + \epsilon_{it} \end{aligned} \tag{4.35}$$

In the second line, the first parentheses contains all the fixed terms, or the fixed effects, while the second contains all the random effects followed by the individual error term.

Specifying a growth model with a cubic component would be done in a similar manner by adding a fourth column to the matrix of factor loadings in Equation (4.30) which would contain the cubic time score, in addition to a fourth mean and individual-specific deviation. However, the more complex the time specification, the more data is required for the model to be identified and estimated. The rule of thumb according to Bollen and Curran (2006) is three waves of data for a linear model, four for a quadratic model, and five for a cubic model or a linear piecewise or spline model. However, this doesn't mean that every single individual has to contribute a minimum of three waves of complete data to estimate a linear growth curve model. A linear model can be identified as long as the majority of individuals have three measurements. It's the same case for quadratic, cubic, or piecewise models.

An alternative extremely flexible time specification that can be easily specified in the SEM framework is the "freed-loading" (Bollen and Curran 2006, 100), or "latent basis" (McArdle and Nesselroade 2014, 107) model where the time scores are freely estimated for all but two time points. The interpretation of the estimated loadings depends on which two time points are chosen for the fixed factor scores. The path diagram for this model is shown in Figure 4.4.

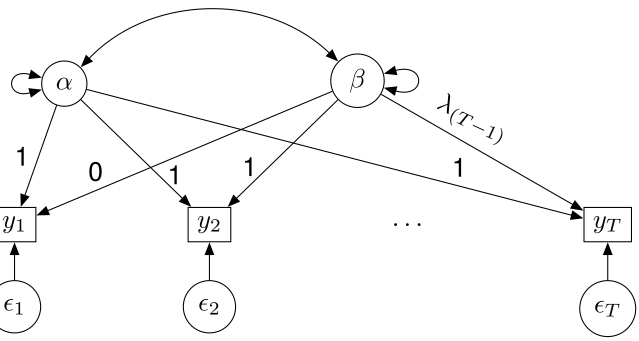

Figure 4.4 – Linear Growth Curve Model with Estimated Loadings

Compared to Figure 4.1, the difference is that the loadings for β as fixed for the first two time points, but are freely estimated for the other T time points. If the first and second time points are fixed, then the interpretation of the other estimated factor loadings is a multiple of the change that occurred between the first two measurement occasions. The last two measurement points can also be chosen for the fixed scores, and in that case the estimated loadings can be interpreted as a fraction of the overall change over time (Bollen and Curran 2006, 100).

This type of model is easily specified in the case of the SEM framework. The factor loadings simply need to be allowed to be freely estimated. The model itself is specified in a similar manner to a linear growth curve model except the loadings, or time scores, in the $\mathbf{\Lambda}$ matrix of Equation (4.27). If we express the complete model matrices as in Equation (4.28), we now have:

$$\begin{pmatrix} y_{i1} \\ y_{i2} \\ \vdots \\ y_{iT} \end{pmatrix} = \begin{pmatrix} 1 & 0 \\ 1 & 1 \\ \vdots & \vdots \\ 1 & \lambda_T \end{pmatrix} \left[\begin{pmatrix} \mu_\alpha \\ \mu_\beta \end{pmatrix} + \begin{pmatrix} \zeta_{\alpha i} \\ \zeta_{\beta i} \end{pmatrix} \right] + \begin{pmatrix} \epsilon_{i1} \\ \epsilon_{i2} \\ \vdots \\ \epsilon_{iT} \end{pmatrix} \tag{4.36}$$

This type of model and time-metric can also be estimated within the multilevel or mixed-effects framework but specifying the model for estimation is more complex (Grimm, Ram, and Estabrook 2017, 237, 242–247).

4.1.3 Incorporating Covariates

In the growth curve models that have been presented so far, there have been no covariates included. Both time-invariant and time-varying covariates can be included in these models. They can be manifest covariates or, in the SEM framework, latent variables. The manner in which these covariates are incorporated into the growth model, however, is not the same. Time-constant covariates, also called level-2 variables, refer to characteristics that are related to the *individual* but that to do not vary with each observation. Time-varying covariates, also called level-1 variables, refer to characteristics that change, or can change, between *observations* of an individual. As such, when they are incorporated into growth curve models, time-varying and time-constant variables are included in different parts of the growth curve model.

Figure 4.1 shows how a time-constant covariate can be incorporated into a simple linear growth curve model. As we can see from the path diagram, when incorporating a time-constant covariate, at least one of the latent factors needs to be regressed on the covariate. When only the intercept or time-constant component of the growth curve is regressed on a time-invariant covariate, it is the same as including the covariate as a fixed effect in the case of a multilevel of mixed-effects regression. When the slope or time-varying component is regressed on a time-constant covariate, it is equivalent to adding an interaction between time and the time-constant variable i.e. one that is measured at the individual level and not at the observation level.

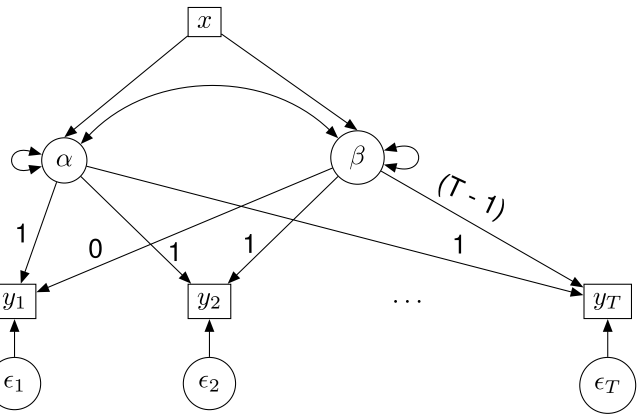

Figure 4.5 – Linear Growth Curve Model with Time-constant Covariate

If we express this model in the notation for multilevel or mixed-effects models, we still have the same overall model as expressed in Equation (4.21). What changes are the α and β components in Equations in (4.22) and (4.23). They now become:

$$\alpha_i = \mu_\alpha + \zeta_{\alpha i} + \gamma_\alpha x_i \tag{4.37}$$

and

$$\beta_i = \mu_\beta + \zeta_{\beta i} + \gamma_\beta x_i \tag{4.38}$$

Equations (4.37) and (4.38) show that a time-constant variable x_i – denoted by the absence of a t subscript – is incorporated directly into the curve parameters α and β. Combining these equations with Equation (4.21) we now have:

$$\begin{aligned} y_{it} =& (\mu_\alpha + \zeta_{\alpha i} + \gamma_\alpha x_i) + \lambda_t(\mu_\beta + \zeta_{\beta i} + \gamma_\beta x_i) + \epsilon_{it} = \\ & (\mu_\alpha + \lambda_t \mu_\beta) + (\gamma_\alpha + \gamma_\beta \lambda_t) x_i + (\zeta_{\alpha i} + \zeta_{\beta i} + \epsilon_{it}) \end{aligned} \tag{4.39}$$

The first parentheses of the second line contain the means of the latent factors. The second contain regressions of the latent factors α and β on the covariate x_i. The final parentheses contain the random part of the model i.e. the error terms.

In SEM matrix notation, we now have a new term to add to Equation (4.27):

$$\mathbf{y_i} = \boldsymbol{\Lambda}\left(\boldsymbol{\mu_\eta} + \boldsymbol{\Gamma}\boldsymbol{x}_i + \boldsymbol{\zeta}_i\right) + \boldsymbol{\epsilon_i} \tag{4.40}$$

The vector $\boldsymbol{x}_i$ contains the values for all the time-invariant covariates for individual i while the matrix $\boldsymbol{\Gamma}$ contains the regression coefficients of $\boldsymbol{\eta}$ regressed on the time-constant covariates. In expanded matrix notation for a linear growth curve model we have:

$$\begin{pmatrix} y_{i1} \\ y_{i2} \\ \vdots \\ y_{iT} \end{pmatrix} = \begin{pmatrix} 1 & 0 \\ 1 & 1 \\ \vdots & \vdots \\ 1 & T-1 \end{pmatrix} \left[\begin{pmatrix} \mu_\alpha \\ \mu_\beta \end{pmatrix} + \begin{pmatrix} \zeta_{\alpha i} \\ \zeta_{\beta i} \end{pmatrix} + \begin{pmatrix} \gamma_{\alpha 1} & \gamma_{\alpha 2} & \cdots & \gamma_{\alpha K} \\ \gamma_{\beta 1} & \gamma_{\beta 2} & \cdots & \gamma_{\beta K} \end{pmatrix} \begin{pmatrix} x_{1i} \\ x_{2i} \\ \vdots \\ x_{Ki} \end{pmatrix} \right] + \begin{pmatrix} \epsilon_{i1} \\ \epsilon_{i2} \\ \vdots \\ \epsilon_{iT} \end{pmatrix} \tag{4.41}$$

Time-varying covariates can also be included in the model. Using the multi-level framework notation, we have the following level 1 equation:

$$y_{it} = \alpha_i + \lambda_t \beta_i + \gamma_t w_{it} + \epsilon_{it} \tag{4.42}$$

Equation (4.42) shows that the time-varying covariates are included *directly*, that is at level 1 or at the level of the observations.

The level 2 equations for α_i and β_i can be either those where there aren't any time-constant covariates include, Equations (4.22) and (4.23), or can incorporate time-constant variables as in Equations (4.37) and (4.38). If we combine Equation (4.42) with Equations (4.37) and (4.38), we get Equation (4.43).

$$\begin{aligned} y_{it} =& (\mu_\alpha + \zeta_{\alpha i} + \gamma_\alpha x_i) + \lambda_t(\mu_\beta + \zeta_{\beta i} + \gamma_\beta x_i) + \gamma_t w_{it} + \epsilon_{it} = \\ & (\mu_\alpha + \lambda_t \mu_\beta) + (\gamma_\alpha + \gamma_\beta \lambda_t) x_i + \gamma_t w_{it} + (\zeta_{\alpha i} + \zeta_{\beta i} + \epsilon_{it}) \end{aligned} \tag{4.43}$$

In the case of the SEM framework, when time-varying covariates are included, the time-varying dependent variable is regressed directly on them as shown in the path diagram in Figure 4.6. The corresponding matrix notation is shown in Equation (4.44).

$$\mathbf{y_i} = \boldsymbol{\Lambda}\left(\boldsymbol{\mu_\eta} + \boldsymbol{\Gamma}\boldsymbol{x}_i + \boldsymbol{\zeta}_i\right) + \boldsymbol{W}\boldsymbol{w}_i + \boldsymbol{\epsilon_i} \tag{4.44}$$

In Equation (4.44), $\boldsymbol{W}$ is a matrix containing the regression coefficients for the time-varying variables in $\boldsymbol{w}_i$. The rest of the terms are the same as in Equation (4.40).

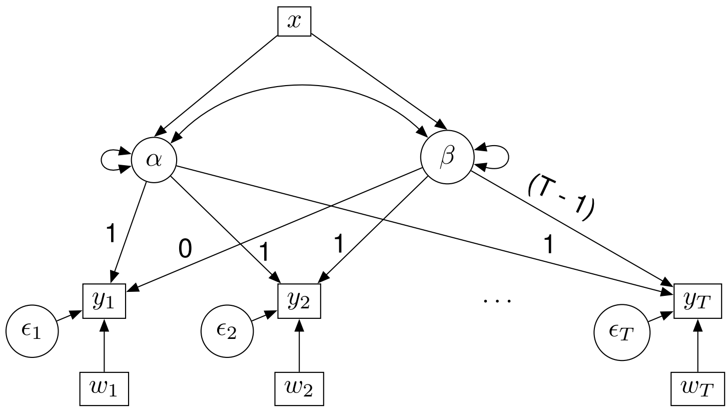

Figure 4.6 – Linear Growth Curve Model with Time-constant and Time-varying Covariates

The one major difference of such models estimated in the SEM framework is that most software by default estimates a different coefficient for each time point. In the case of multilevel model estimation, the effects of the time-varying covariates are averaged across all time points. This can also be accomplished in SEM software by constraining the regression parameters for the time-varying variables to be equal over all time points to give an equivalent model (Grimm, Ram, and Estabrook 2017, 190).

4.1.4 Binary and Ordinal Dependent Variables

So far, only growth curve models with continuous dependent variables have been described. The most apparent change in the model specification itself is that the residual errors, corresponding to the ϵ terms, are no longer estimated. In the case of the logistic function the residual variance of the distribution is fixed and is equal to $\frac{\pi^2}{3}$. In the case of a probit link, the residual variance is fixed to 1. Thus, there is no estimation of the variance of the level-1 residual error; that is the observation-level residual variance is considered as fixed. The path diagrams also remain the same except that no residual error is estimated at the observation level. The notation of the manifest variables also changes. A more compact notation specifies that the indicator is not continuous by putting a line through a square representing a manifest variable as in Figure 4.7.

Another option is to explicitly show, as in Figure 4.8 that a continuous latent variable is being estimated from categorical indicators following McArdle and Nesselroade (2014, 243).

As latent growth curve models in the SEM framework are simply a specific type of confirmatory factor analysis model, the estimation techniques developed to estimate factor models with noncontinuous indicators can also be used to estimate latent growth curve models with ordinal or binary dependent variables. Thus the weighed least squares estimator or the full-information maximum likelihood

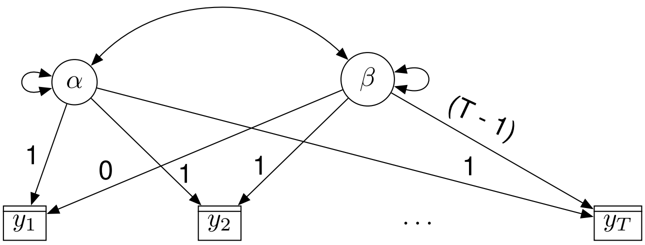

Figure 4.7 – Representing Binary Dependent Variables
Compact notation

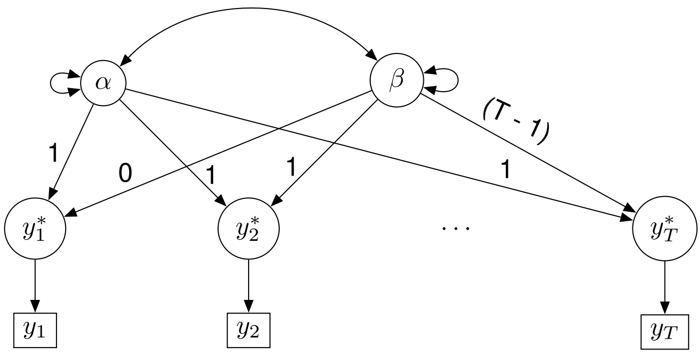

Figure 4.8 – Representing Binary Dependent Variables
Extended notation

estimators presented in Section 4.1.1 can be used to estimate growth curve models within the SEM framework. The principal difference is that in the case of many latent variables, especially in the case of a "curve-of-factors" model (described below) for instance, the computation can become rather time-consuming when using a full-information maximum likelihood estimator. As the dimension of the integral in Equation (4.17) increases with the number of latent variables, it becomes more difficult to calculate its numerical approximation. Thus, the different growth curve models that can be estimated for continuous manifest dependent variables in the SEM framework can also be estimated in the case of categorical (binary or ordinal) dependent variables. However, the computation time may be longer as the methods used for model estimation are more computationally intensive than in the case of a continuous dependent variable though convergence generally isn't much of an issue especially with full-information maximum likelihood (Newsom and Smith 2020).

4.1.5 Extensions

The models presented here are fairly standard growth curve models and there are further extensions that can be made in order to test even more complex theoretical frameworks or model more complex trajectories of change over time. A relatively

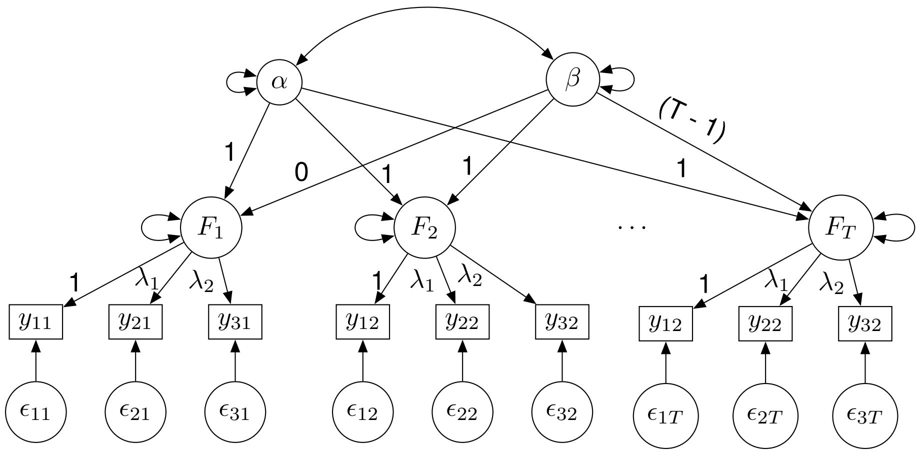

Figure 4.9 – Curve-of-factors Linear Growth Curve Model

straightforward extension within the SEM framework is the "curve-of-factors" model (McArdle 1988) where the change process models change in a latent variable over time rather than a manifest variable as shown in the path diagram in Figure 4.9. There is however an additional issue when specifying such model compared to more standard latent curve models. For the results to actually be interpretable, it is necessary to make sure that the latent factors are actually measuring the same thing over time. Therefore, as a preliminary step *before* estimating a growth curve model, factorial invariance needs to be assessed (McArdle and Nesselroade 2014, 207–229; Grimm, Ram, and Estabrook 2017, 348–350). Typically, *weak* invariance, where the loadings are constrained to be equal over time, is considered insufficient. We need *strong* invariance which constrains the item means, or intercepts, to be equal across measurements in addition to the factor loadings (Meredith 1993). Strong invariance is generally considered to be sufficient to consider that the growth process is modelling change over time for the same latent construct (Bollen and Curran 2006, 256; McArdle and Nesselroade 2014, 232; Grimm, Ram, and Estabrook 2017, 348).

Another extension of latent growth curve models are multivariate growth curve models. An example path diagram is shown in Figure 4.10. Multivariate growth curve models allow the latent shape factors to be correlated which in a sense measures how the variables evolve over time together (Bollen and Curran 2006, 201). It is also possible to regress the latent factors on each other to test temporal precedence for instance (Grimm, Ram, and Estabrook 2017, 181–182). They also allow for the dependent variables to be regressed on each other in the case of the cross-lagged growth curve models or auto-regressive latent trajectory models (Bollen and Curran 2004; 2006, 207–218). However, cross-lagged models can have trouble converging in the case of a continuous outcome and having good starting values becomes more important (Grimm, Ram, and Estabrook 2017, 429).

Another model which is similar to the auto-regressive latent trajectory models proposed by Bollen and Curran (2004, 2006) is the latent change score model and

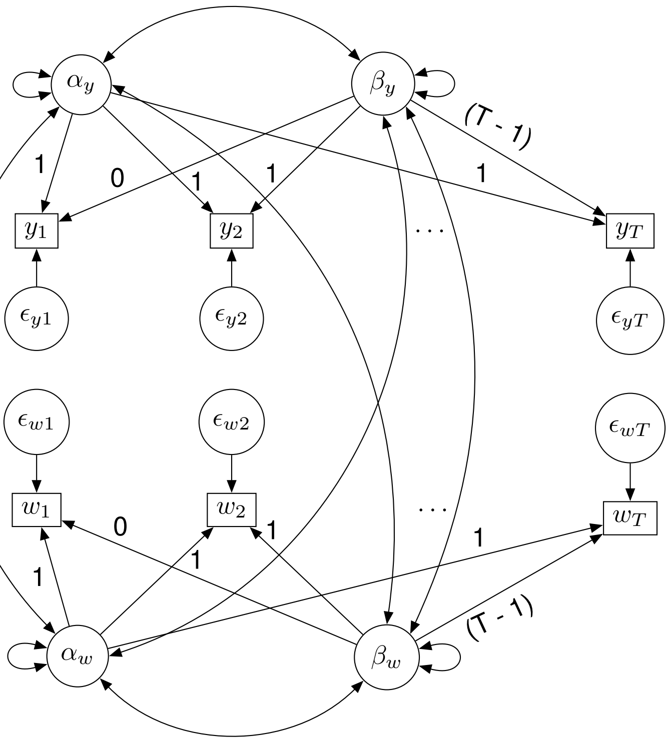

Figure 4.10 – Bivariate Growth Curve Model

its bivariate or multivariate extension (McArdle 2009; McArdle and Nesselroade 2014, 291–300). This model was explicitly designed following the five rationales for longitudinal research set out by Nesselroade and Baltes (1979), namely analysing intraindividual and interindividual change and their causes for interrelated processes. The model shares many commonalities with the auto-regressive latent trajectory model, but it differs in one crucial aspect. Rather than modelling the growth curve using the manifest variables directly, the latent parameters, for example the slope and intercept, reflect the *difference* in the dependent variable between measurement occasions.

In the models presented in Section 4.1.2, any non-linearity in the trajectories has been introduced through either adding additional factors to the model, such as in the quadratic growth model (Figure 4.3 and Equation (4.35)), or by leaving the factor loadings of the change component to be freely estimated as in the case of the free-loading model (Figure 4.4 and Equation (4.36)). However, another alternative for introducing non-linearity in trajectories is by specifying parametric functions to express change over time (Bollen and Curran 2006, 106). For example, instead of specifying a polynomial function of time, such as a quadratic one, an alternative function from the exponential family can be chosen. The advantage of using such functions over regular polynomial functions to model change over time in a variable is the possibility of having change that, over time, reaches asymptotic limits. In other words functions in the exponential family can be used to model change over time where there are floor or ceiling effects, for instance, which is not the case for polynomial functions which always tend towards infinity (Bollen and Curran 2006, 108).

However, estimating these models is not particularly straightforward especially in the SEM framework as it requires estimating non-linear relationships between the latent variables and the dependent variable. To illustrate this, as shown in Equation (4.21), a linear growth curve model can be expressed as:

$$y_{it} = \alpha_i + \lambda_t \beta_i + \epsilon_{it} \tag{4.45}$$

while a growth model following an exponential for example would have the following form:

$$y_{it} = \alpha_i + \beta_i \left(1 - e^{-\gamma \lambda_t}\right) + \epsilon_{it} \tag{4.46}$$

where γ can be considered as a shape parameter determining the rate of change between two time points with β_i representing the overall rate of change between the initial time point and the end (107). Estimating such a non-linear model in the SEM framework requires some effort in setting up model constraints in order to use a Taylor series approximation to estimate the model as was shown in Browne and Toit (1991) and Browne (1993). Following this, it is possible to express the exponential function in terms of a polynomial model allowing it to be estimated within the SEM framework (see du Toit and Cudeck 2001, Grimm and Ram 2009, or Grimm, Ram, and Estabrook 2017, 298–299 for examples). Nonlinear growth curve models can also be extended with cyclical functions such as the cosine or sine and even be combined with linear or quadratic models (Hipp et al. 2004; Bollen and Curran 2006, 109–110).

Another extension that can be implemented, and which is more easily estimated in the SEM framework, is growth mixture modelling (GMM). These models take the estimated latent factors describing the trajectory and try to classify them into a predetermined number of classes. This model can be thought of as a combination of factor analysis – as latent growth curve models are a special case of factor analysis – and latent profile analysis. In other words, a more general latent variable model is created by combining two special cases as described in Table 4.1.

Care needs to be taken when estimating and interpreting GMM models as they are more of an exploratory approach (McArdle and Nesselroade 2014, 309; Grimm, Ram, and Estabrook 2017, 139). While the number of classes is chosen a priori, it is possible to compare models using fit indices, or other diagnostics, to determine which model best represents the data (Grimm, Ram, and Estabrook 2017, 157–158; Newsom 2015, 285). An additional step for verification is testing the number of classes by randomly partitioning the data and verifying that the number of classes chosen also provides the best solution for the subsets (Grimm, Mazza, et al. 2017). As for the interpretation of the results from these models, care needs to be taken as even if the model identifies different classes, they may be artefacts related to improperly measured variables or non-normally distributed variables rather than actually identifying different classes (Bauer and Curran 2003, 2004; Bauer 2007;

Ram and Grimm 2009, 573). Consequently, a major concern when interpreting results from a growth mixture model is whether the groups that are identified are actually different sub-populations rather than issues due to violated assumptions or data issues.

4.1.6 Conclusion

In conclusion, latent growth curve models are a very flexible tool for the analysis of longitudinal data. The extensions offered, especially when estimating such models in the SEM framework, allow for the estimation of potentially very complex models that can test numerous hypotheses or model processes simultaneously. Time can also be treated flexibly as it is possible to specify potentially complex, non-linear change over time. However, latent growth curve models make certain assumptions, namely that the underlying process that is being modelled is a continuous one both in relation to time and the underlying latent variables describing the trajectory.

In the application of these models to a vulnerability framework, vulnerability is treated as a continuous scale. Change over time is also treated as being continuous rather than discrete. In other words, vulnerability is not viewed as a state but rather as an underlying continuous measure that can change instantaneously over time. *How* vulnerability is thought to change over time can be changed and tested as it is possible to evaluate which specification of change over time best describes the patterns in the data.

As for the interpretation of growth curve models in the context of vulnerability, more particularly within the framework presented in Section 3.3 derived from that of Spini et al. (2013) and Spini et al. (2017), the main elements of interest are the latent parameters. Standard growth curve models are best suited for describing trajectories after the occurrence of a stressor. In the case of a linear model, the intercept factor corresponds to the level of vulnerability at whichever time point is designated as time zero. If time zero is defined as being the first point in time after an individual experiences a stressor, then it is the mean level of vulnerability immediately after the occurrence of a stressor. If, for example, the dependent variable is an indicator of psychological distress, the intercept factor will be the mean of psychological distress at the initial time point.

The slope factor, which estimates the mean of change over time, can be interpreted as being a measure of coping or recovery. If we continue with the example of psychological distress, the slope factor can be a measure of how well individuals cope with a stressor. If there is little change over time, or even a decline, then individuals can be considered to have coped or possibly even begun to recover. However, the simpler the manner in which time is treated, the harder it is to estimate non-linear trajectories that can for instance rise initially, and fall later on, such as a quadratic, spline, or latent basis models. However, interpreting the latent parameters can become more complex especially in the case of quadratic or latent basis models.

When taking into account individual covariates, which represent individuals' resources, we can examine their association with the initial level of vulnerability, that is the regression coefficients of time-constant variables on the intercept factor. The time-varying latent factors can also be regressed on time-constant covariates. This allows for comparing the trajectories of coping, and possibly recovery, between individuals based on their time-constant characteristics. This allows for analysing between-individual differences and seeing whether certain categories of individuals are more vulnerable relative to other categories.

Time-varying covariates are slightly more complicated to interpret as the observations of the manifest variable are directly regressed on them. Continuing with the example of psychological distress, a possible time-varying covariate could be, for instance, an indicator of workplace well-being. The interpretation of the latent factors as well as the associations of the latent factors with time-constant covariates changes when including time-varying variables. The means of the latent factors describing the trajectory become *conditional* means. In other words, the latent factors describe the trajectory of the dependent variable once the associations between the dependent variable and the time-varying covariates have been taken into account. The same is true when there are time-constant covariates. The association of these covariates with the latent factors also become conditional once the time-varying covariates are included. That is, the regressions of the latent factors on the time-constant variables can be interpreted as the association of the variable with the growth trajectory once the associations between the dependent and time-varying independent variables are taken into account. The interpretation of growth curve models within a vulnerability framework will be further illustrated in the first application modelling vulnerability to unemployment in the aftermath of the Great Recession in the UK and Switzerland in Chapter 6.

As shown in Section 4.1.5, growth curve models can be substantially extended. While the application of growth curve models in this thesis is focused on a single categorical dependent variable, and thus univariate growth curve models, it is possible to utilize the extensions to explore more complex approaches to vulnerability. Vulnerability is a multidimensional concept and thus modelling processes using factors with multiple indicators is a logical, and relatively straightforward extension. Additionally, multivariate growth curve models can be a useful tool in the study of vulnerability especially if the interest is in analysing spillovers between multiple domains. Multivariate growth curve models allow for analysing either parallel processes of vulnerability and/or investigating change in different domains in response to an increase in vulnerability in another. Finally, there is the option of using growth mixture models either as an exploratory tool, or if there are underlying unmeasured groups that are hypothesized. However, the results of models should be interpreted with caution in relation to the potential caveats of growth mixture modelling as previously examined in Section 4.1.5.

Nevertheless, growth curve models represent one manner of modelling vulnerability with longitudinal data with latent variables. In the following section, latent class analysis, along with its longitudinal extensions, will be presented as an alternative manner of modelling vulnerability processes. Modelling vulnerability with this special case of latent variable model (see Table 4.1) leads us to treat vulnerability differently by considering it in relation to a discrete set of *classes*. However, what these classes represent, especially in the longitudinal case, depends on how we choose to model the process of vulnerability over time which will be considered in more detail.

4.2 Latent Class Models

Latent class models are, in a sense, the categorical counterpart to factor analysis models. In Table 4.1, latent class models represent the special case of general latent variable models where the indicator, or manifest, variables are categorical and the latent variables are also categorical. In this section, the general form of latent class models will be presented with a focus on the more recent latent variable model formulation rather than the log-linear formulation. Different methods for incorporating covariates into latent class analysis will also be discussed. Finally, longitudinal extensions/variants of latent class models will also be presented.

4.2.1 An Introduction to Latent Class Models

Latent class models, at least in the canonical form, are a latent variable method designed for the analysis of categorical data. In latent class models, the manifest or observed variables are categorical and the same is true for the underlying latent variables. Thus, unlike latent variable models with noncontinuous indicators and continuous outcomes, the latent variable is assumed to take on a limited number of *discrete* values which represent the different latent *classes*. In earlier approaches, latent class models were expressed in terms of cross-tables (Lazarsfeld and Henry 1968) and later log-linear models (Goodman 1974b, 1974a; McCutcheon 2002). In this approach, an observed pattern in the distribution of responses to categorical variables is hypothesized to be explained or related to an unobserved latent variable. Based on the observed information, unobserved or latent parameters describing the model need to be estimated: the item response probabilities and the latent class frequencies. Lazarsfeld and Henry (1968, 46) summarize this in a table similar to Table 4.5.

Latent Class Freq.	γ_1	γ_2	$\cdots$	γ_c
Item-response prob. for item 1	ρ_{11}	ρ_{12}	$\cdots$	ρ_{1c}
Item-response prob. for item 2	ρ_{21}	ρ_{22}	$\cdots$	ρ_{2c}
$\cdots$	$\vdots$	$\vdots$	$\ddots$	$\vdots$
Item-response prob. for item j	ρ_{j1}	ρ_{j2}	$\cdots$	ρ_{jc}

Table 4.5 – Parameters to Estimate in Latent Class Models

This table shows that there are two main types of parameters that are estimated: the γ parameters and the ρ parameters. The γ parameters are the frequencies or proportion of observations in a given latent class c. By definition the γ terms sum to one i.e. $\sum_{c=1}^{C} \gamma_c = 1$ where C is the number of latent classes. The ρ terms represent *conditional* probabilities of responding "yes" to a binary item. They are conditional because it is the probability of responding yes *given* that the person responding belongs to a specific latent class c.

This brings us to one of the main assumptions behind latent class models, and indeed factor analysis models: the local independence assumption (Lazarsfeld and Henry 1968, 22; Collins and Lanza 2010, 44). Under the local independence assumption, it is assumed that the indicator or manifest variables are independent *conditional* on being related to the same underlying latent variable. In other words, it is assumed that any relationship we observed between these manifest variables is due to them being related to the same underlying latent variable. This leads to some useful properties in the case of latent class models. First it means that "*[t]he within class probability of any pattern of responses to any set of items is the product of the appropriate marginal probabilities.*" (Lazarsfeld and Henry 1968, 22; emphasis in original) In other words, if we want to know the probability of an individual responding yes to items 1 and 2 in Table 4.5 given that they belong to the first latent class, this corresponds to simply multiplying together ρ_{11} and $\rho 21$. Thus, for a given class c, the probability of observing a specific vector $\boldsymbol{y}$, or column, of responses to J items as in Table 4.5 is the product of all the conditional, or item-response, probabilities within a specific class c i.e. $\boldsymbol{y}_c = \prod_{j=1}^{J} \rho_{jc}$. Another result of the assumption of local independence is that the probability of responding to a specific item j overall can be defined as a weighted sum of the class-specific item-response probabilities i.e. $\rho_{j\cdot} = \sum_{c=1}^{C} \gamma_c \rho_{jc}$. For instance, the overall probability of somebody responding yes to the first item in Table 4.5 is $\rho_1 = \sum_{c=1}^{C} \gamma_c \rho_{1c}$.

So far, only the case where the indicator variables are dichotomous has been presented. Incorporating polytomous variables – variables with more than two response categories – is relatively straightforward. Using dummy-coding, it is possible to create $K-1$ binary variables, where K is the number of categories in the polytomous variable, and treat the model as if there were multiple binary indicators. An additional property is that the K conditional probabilities of a polytomous variable j within a class c sum to one, in other words $\sum_{k=1}^{K} \rho_{kjc} = 1$ (Collins and Lanza 2010, 41).

Putting this all together, and following the notation of Collins and Lanza (2010, 41), it is possible to express a latent class model as the probability of observing a vector of responses $\boldsymbol{y}$ in relation to a set of categorical indicators as:

$$P(\boldsymbol{Y} = \boldsymbol{y}) = \sum_{c=1}^{C} \gamma_c \prod_{j=1}^{J} \prod_{r_j=1}^{R_j} \rho_{j,r_j|c}^{I(y_j=r_j)} \tag{4.47}$$

The product $\prod_{r_j=1}^{R_j} \rho_{j,r_j|c}^{I(y_j=r_j)}$ serves to multiply together the item-response probabilities, or conditional probabilities, $\rho_{j,r_j|c}$ for the R_j response categories of a categorical variable j for a specific class c. The indicator function $I(y_j = r_j)$ takes the value one when the observed response to an indicator y_j is equal to a specific response category r_j. It serves a convenience function to ensure that the correct item-response probabilities for each of the categories of a variable j are multiplied together. The second product – $\prod_{j=1}^{J}$ – multiplies the item-response probabilities for each j indicator, within a specific latent class c, together. This corresponds to multiplying the elements in the rows of a single column of Table 4.5 together. For each class (column), these probabilities are then multiplied by the proportion of observations in a given class c, γ_c, and then everything is added together to obtain the overall probability of observing a response pattern $\boldsymbol{y}$ across all of the C latent classes.

Notes on Model Estimation

Latent class models are estimated using the expectation maximization (EM) algorithm (Dempster et al. 1977) which is a maximum likelihood estimation technique although other maximum likelihood estimation techniques specifically designed to estimate latent class models had been proposed earlier (Goodman 1974a, 1974b; Haberman 1974, 1976). This is a more general algorithm that can be used not only to estimate latent class models, but the more general class of finite mixture models where the indicator variables can be continuous, or categorical, or a combination thereof. Just as in the case of structural equation modelling, missing data in relation to the indicators can be dealt with directly using full-information maximum likelihood (FIML) estimation (Collins and Lanza 2010, 81).

One specific issue with estimating latent class models is that the EM algorithm has a tendency to converge to local rather than global minima especially in the case of potentially under-identified models (McCutcheon 2002, 65; Vermunt and Magidson 2002, 97). The degree to which a latent class model is identified depends on observable information such as the degrees of freedom, the sample size, the number of latent classes, data sparseness, but also on the unobserved strength of the relationship between the latent variables and the associated indicator variables (Collins and Lanza 2010, 92).

Typically, this problem is attenuated by estimating the model with multiple sets of random starting values, then subsequently estimating, or partially estimating, the model for each set of starting values. Then the models whose starting values yielded the smallest log-likelihood are either estimated, or estimated to convergence in the case of partial estimation, and the analysis is then based on the model with smallest log-likelihood. If different starting values lead to the same minimum estimated log-likelihood, then it is more likely that the estimation algorithm has found a global maximum.

One side-effect of using random starting values is that the order of the classes can change with the starting values. This is also called “label-switching.” (Chung et al. 2004; Collins and Lanza 2010, 94) As an example, let’s assume we have a model with two latent classes and a two binary indicators. In the first class, the item-response probabilities are 0.8 and 0.2 for the first indicator and 0.45 and 0.55 for the second indicator. In the second class, the item-response probabilities are 0.3 and 0.7 for the first indicator and 0.75 and 0.35 for the second indicator. Depending on the starting values, the estimated item-response probabilities for the first class can end up being, 0.3, 0.7, 0.75, and 0.35 rather than 0.8, 0.2, 0.45, and 0.55. However, this has no consequences for the actual results, and is only a problem when comparing results from different starting values in that it might suggest that different starting values lead to different solutions.

Another aspect of model estimation that needs to be taken into account, and which is also the case for other latent variable models, is that the number of classes needs to be chosen beforehand. Choosing the number of classes can be driven by theory. For instance, a researcher could be testing a theory which hypothesizes that responses to a set of questions should differ between individuals conditional on them being in either an unobserved “vulnerable” latent class or in an unobserved “non-vulnerable” latent class. However, in other cases there may be no strong theoretical grounding for the choice of the number of latent classes. In this case, the number of latent classes to use can potentially be determined using model fit indices. The simplest solution is to use relative fit indices such as the Akaike information criteria, AIC, (Akaike 1974) or the Bayesian information criteria, BIC (Schwarz 1978).

4.2.2 Including Covariates

So far unconditional latent class models, or latent class models without covariates, have been presented. However, in many cases there is an interest in trying to see whether observed characteristics can explain differences in the probability of an individual belonging to a specific latent class.

Using the notation of Collins and Lanza (2010, 153), a latent class model with covariates can be expressed as follows:

$$P(\boldsymbol{Y} = \boldsymbol{y}|X = x) = \sum_{c=1}^{C} \gamma_c(x) \prod_{j=1}^{J} \prod_{r_j=1}^{R_j} \rho_{j,r_j|c}^{I(y_j=r_j)} \tag{4.48}$$

Compared to Equation (4.47), there are two main differences. The first is that we no longer *only* estimate the probability of observing a vector of responses $\boldsymbol{y}$. Now, a *conditional* probability is estimated as the probability of observing $\boldsymbol{Y} = \boldsymbol{y}$ depends on the value of covariate X. Looking more closely at the expression in Equation (4.48), we see that the covariate X only influences the proportion of individuals in a latent class c – also called the latent class prevalence – but not the item-response probabilities. Thus it is assumed that covariates do not influence the probability of an individual providing a specific response r_j for an indicator j. This is the measurement invariance assumption which assumes that the latent the vector of $\boldsymbol{y}$ responses is independent of the covariate x. Violating this assumption can lead to biased results as the model is then misspecified (Bolck et al. 2004, 4; Collins and Lanza 2010, 154). This is why certain researchers advocate estimating the latent class models separately from the model relating the latent classes to covariates (Vermunt 2010, 467).

As for the $\gamma_c(x)$ term, it corresponds to the conditional probability of observing an individual belonging to a specific latent class $L = c$ in relation to the value x of covariate X. Formally, this can be expressed as (Collins and Lanza 2010, 153):

$$\gamma_c(x) = P(L = c|X = x) = \frac{e^{\beta_{0c}+\beta_{1c}x}}{1 + \sum_{c=1}^{C-1} e^{\beta_{0c}+\beta_{1c}x}} \tag{4.49}$$

The expression in Equation (4.49) corresponds to that of a multinomial logistic regression of the latent variable L, the latent classes, with C different categories on the covariate X.

Generally, there are two approaches to estimating latent class models with covariates. The first is the “one-step” or “single-step” estimation technique where the latent class model and the effects of the covariates are jointly estimated. This approach while more efficient from a statistical point of view, is also more computationally intensive (Bolck et al. 2004; Vermunt 2010).

The second approach is the so-called “three-step” approach. In the first step, a latent class model without covariates is estimated. In the second, individuals or observations are assigned to the different latent classes based on their responses to the observed indicators. In the final step, the latent class assignment is regressed on the covariates using, typically, multinomial logistic regression.

Concerning the second step, latent class assignment, there are multiple approaches that can be taken. All the assignment approaches start from the same point which is the calculation of the posterior probabilities of latent class membership. In other words, the aim is to calculate the probability of observing an individual in a specific latent class c given their responses to the indicators variables or $P(L = c|\boldsymbol{Y} = \boldsymbol{y})$ where L is the latent variable, $\boldsymbol{Y}$ the vector of responses and $\boldsymbol{y}$ the observed response vector. Using Bayes' theorem, this probability can be expressed as:

$$P(L = c|\boldsymbol{Y} = \boldsymbol{y}) = \frac{P(\boldsymbol{Y} = \boldsymbol{y}|L = c)P(L = c)}{P(\boldsymbol{Y} = \boldsymbol{y})} \tag{4.50}$$

The denominator of Equation (4.50) is the same as Equation (4.47) that is the probability of observing a certain set of responses. As for the numerator, the probability of observing a certain latent class c, $P(L = c)$ corresponds to the latent class frequency in Table 4.5 and is just γ_c or the latent class frequency for a given class c. The final part of the expression, $P(\boldsymbol{Y} = \boldsymbol{y}|L = c)$ is equivalent to multiplying all the item-response probabilities of a single class together, or all the ρ terms in a column of Table 4.5. This corresponds to the products in Equation (4.47) and therefore

$$P(\boldsymbol{Y} = \boldsymbol{y}|L = c) = \prod_{j=1}^{J} \prod_{r_j=1}^{R_j} \rho_{j,r_j|c}^{I(y_j=r_j)}$$

Putting everything together, the individual posterior probability of belonging to a certain latent class c conditional on the observed responses $\boldsymbol{y}$ is:

$$P(L = c|\boldsymbol{Y} = \boldsymbol{y}) = \frac{\gamma_c \prod_{j=1}^{J} \prod_{r_j=1}^{R_j} \rho_{j,r_j|c}^{I(y_j=r_j)}}{\sum_{c=1}^{C} \gamma_c \prod_{j=1}^{J} \prod_{r_j=1}^{R_j} \rho_{j,r_j|c}^{I(y_j=r_j)}} \tag{4.51}$$

One issue is choosing how to assign individuals to a latent class as it is possible for individuals to have a non-zero probability of being assigned to multiple classes. The most common, and simplest, approach to latent class assignment is “modal” assignment (Goodman 2007; Vermunt 2010). With modal assignment, individuals are assigned to the latent class for which the probability $P(L = c|\boldsymbol{Y} = y)$ is greatest. Another option is to randomly assign individuals to each class based on the distribution of their posterior probabilities of belonging to each of the latent class c (Goodman 2007); this is the random assignment approach. Another assignment method is proportional assignment. In proportional assignment, each individual is assigned to each latent class with a weight w corresponding to $P(L = c|\boldsymbol{Y} = y)$ i.e. the probability of belonging to a specific class c.

The third step is regressing the latent class assignment on the covariates using a multinomial regression. In the case of modal and random assignment, each individual corresponds to one case in the resulting data set used for estimation of the multinomial model. In the case of proportional assignment, each individual will have C records, where C is the total number of latent classes, each with a weight w corresponding to the conditional probability, $P((L = c|\boldsymbol{Y} = y)$, of being assigned to a specific class c based on the observed responses $\boldsymbol{y}$.

The problem with the three-step approach is that the results are often biased when compared with a one-step approach (Collins 2001; Bolck et al. 2004; Vermunt 2010; Asparouhov and Muthén 2014). The problem is that these methods do not properly take into account any possible error in the assignment process. Outside of an extremely unlikely situation in which each individual has a probability of one of being assigned to a specific latent class c, and zero for being assigned to any other class, there is always the risk of improperly classifying an individual into a latent class that is not their *true* latent class.

One solution to this problem is the “BCH” method proposed by Bolck et al. (2004) and improved by Vermunt (2010). This method is, in a sense, an extension of the proportional assignment approach except the weights are calculated using the inverse of the classification error rate matrix (Vermunt 2010; Bolck et al. 2004; Asparouhov and Muthén 2014). Then, just like in the case of the proportional assignment model, each individual has C cases in the data set with the corresponding weights calculated from the inverse matrix. There are two problems that need to be taken into account when using this method. The first is that the weights can be negative and therefore software that can estimate regressions with negative weights needs to be used. The second is that the observations in the data set are no longer independent from each other as they are clustered within individuals. Using robust or sandwich standard errors can reduce this problem but is potentially more conservative than the single-step approach (Vermunt 2010).

Another approach proposed by Vermunt (2010) is the maximum-likelihood BCH method. Where it differs compared to the weighted regression approach is that it re-estimates a latent class model with covariates, as in Equation (4.48), but it reuses the estimated item-response probabilities from the first step (so they aren’t estimated again), taking into account classification error, while estimating the effect of the covariates on the latent class prevalences which corresponds to Equation (4.49).

An extension of the random assignment approach proposed by Goodman (2007) is the “pseudo-class” assignment approach (Bandeen-Roche et al. 1997; Wang et al. 2005; Bray et al. 2015). The random assignment procedure rather than just being applied once is applied multiple times, usually around 20 (Wang et al. 2005; Bray et al. 2015), and multiple regression models are estimated for each set of random assignments. The estimates of the models are then combined using the rules for multiple imputation from Rubin (1987).

4.2.3 Longitudinal Extensions

There are two main manners to apply latent class models to longitudinal data. The first is longitudinal or repeated-measures LCA (Collins and Lanza 2010, 182). This longitudinal extension is straightforward. In the case of repeated measurements of a set of categorical indicators, a latent class model is fitted using *all* of the individual observations over time for each indicator.

Latent Class Freq.	γ_1	γ_2	$\cdots$	γ_c
Item-response prob. for item 1 at time 1	ρ_{111}	ρ_{121}	$\cdots$	ρ_{1c1}
Item-response prob. for item 1 at time 2	ρ_{112}	ρ_{122}	$\cdots$	ρ_{1c2}
Item-response prob. for item 2 at time 1	ρ_{211}	ρ_{221}	$\cdots$	ρ_{2c1}
Item-response prob. for item 2 at time 2	ρ_{212}	ρ_{222}	$\cdots$	ρ_{2c2}
$\cdots$	$\vdots$	$\vdots$	$\ddots$	$\vdots$
Item-response prob. for item j at time t	ρ_{j1t}	ρ_{j2t}	$\cdots$	ρ_{jct}

Table 4.6 – Parameters to Estimate in Latent Class Models

If we take Table 4.5 describing the parameters in a latent class model, in the longitudinal case we would have a table similar to Table 4.6. What this shows is that the latent classes in longitudinal LCA group together responses to different indicators over time. As such, the latent classes can be considered as describing changes in response patterns to the indicator variables over time. These models can also incorporate covariates as in the case of cross-sectional latent class models if the aim is to explain differences in trajectories between groups of individuals. Longitudinal LCA is relatively similar to growth mixture models (cf. Section 4.1.5) in that it classifies individual trajectories over time. However, unlike growth curve models, change over time is not expected to follow a predefined functional form (linear, quadratic, piecewise, etc.). Longitudinal LCA is also extremely similar to the combination of sequence analysis and clustering. Barban and Billari (2012) show that longitudinal LCA and sequence analysis produce similar results when analysing trajectories over time, though each method has advantages and disadvantages over the other. However, one potential major advantage is that LCA, being a maximum likelihood method, can utilize full-information maximum likelihood estimation to deal with missing information on the dependent variable with fewer assumptions compared to sequence analysis. Longitudinal LCA, as well as growth mixture models and sequence analysis, can be considered as holistic approaches as they classify entire trajectories into groups.

Another extension of latent class models for longitudinal data is latent transition analysis (LTA) (Collins and Lanza 2010, 187). The main difference between repeated-measures LCA and LTA is that LTA models movements or *transitions* between different latent classes, or states, over time. The fundamental expression of a latent transition models is provided by Collins and Lanza (2010, 198):

$$P(\boldsymbol{Y} = \boldsymbol{y}) = \sum_{c_1=1}^{C} \cdots \sum_{c_T=1}^{C} \gamma_{c_1} \tau_{c_2|c_1} \ldots \tau_{c_T|c_{T-1}} \prod_{t=1}^{T} \prod_{j=1}^{J} \prod_{r_{j,t}=1}^{R_j} \rho_{j,r_j,t|c_t}^{I(y_{j,t}=r_{j,t})} \tag{4.52}$$

The main difference between Equations (4.47) and (4.53) is that time, t, now plays a role. We see it with the item-response probabilities which now vary not only by class c but also by time. The $\rho_{j,r_j,t|c_t}$ is now as if there were T, where T is the number of time points, different variants of Table 4.5. The other major difference is the latent class probabilities or prevalences. The prevalences for the first time point, γ_{c_1} are the same as in the case of LCA. The difference is that the latent class prevalences for all time points $t > 1$, the τ terms are now conditional on the latent class prevalence for the previous time point $t-1$. This corresponds to a first-order Markov process (219) as the proportion of individuals in a latent class at a certain time point t is dependent on the proportion of individuals that were in a latent class a $t-1$.

One of the aims of LTA is to estimate whether individuals move between different latent classes over time. However, one issue is that the item-response probabilities, the ρ terms, do not necessarily have to remain the same over time. This means that the interpretation of the latent classes can change over time and LTA can be used as a method to assess the stability or change of latent classes over time as well. However, if the aim is to assess individual transitions between classes over time, this can potentially be a hindrance. To deal with this, it is possible to constrain the item-response probabilities to be equal over time. This guarantees that the interpretation of the latent classes remains the same over time and thus the model allows for analysing transitions between different classes that are time-invariant and thus facilitates interpretation of the results. This is analogous the requirement of measurement/factorial invariance that was presented for curve-of-factors growth curve models in Section 4.1.5. Nevertheless, it may be of interest to allow the classes to vary over time as it may be possible that certain classes can appear and disappear.

Just like it is possible to incorporate covariates in LCA, the same is also true for LTA. In this case, the expression becomes (Collins and Lanza 2010, 242):

$$P(\boldsymbol{Y} = \boldsymbol{y}|X = x) = \sum_{c_1=1}^{C} \cdots \sum_{c_T=1}^{C} \gamma_{c_1}(x) \tau_{c_2|c_1}(x) \ldots \tau_{c_T|c_{T-1}}(x) \prod_{t=1}^{T} \prod_{j=1}^{J} \prod_{r_{j,t}=1}^{R_j} \rho_{j,r_j,t|c_t}^{I(y_{j,t}=r_{j,t})} \tag{4.53}$$

As in Equation (4.48), the covariates do not influence the item-response probabilities, but only the latent class prevalences. The latent class prevalences for the first time point, $\gamma_{c_1}(x)$ are estimated using a multinomial logistic regression as in

Equation (4.49). The $\tau_{c_T|c_{T-1}}(x)$ terms are also estimated using a multinomial logistic regression, but the form changes (Collins and Lanza 2010, 244):

$$\tau_{c_T|c_{T-1}}(x) = \\ P(L_t = c_t|L_{t-1} = c_{t-1}, X = x) = \frac{e^{\beta_{0c_t|ct-1}+\beta_{1c_t|ct-1}x}}{1+\sum_{c=1}^{C-1} e^{\beta_{0c_t|ct-1}+\beta_{1c_t|ct-1}x}} \quad (4.54)$$

Each $\tau_{c_T|c_{T-1}}(x)$ is estimated with C regressions as each possible previous latent class needs to be taken into account in the $\tau_{c_T|c_{T-1}}$. This means that in a LTA model with two time points and three classes, there will be one regression to estimate, γ_{c_1}, and three regressions to estimate $\tau_{c_2}|\tau_{c_1}$. Thus, as the number of time points and number of classes increases, so does the number of regressions that need to be estimated making LTA models potentially computationally complex. In fact, each additional time point makes the model estimation exponentially more complex (189) which makes it very difficult, and sometime unfeasible, to estimate LTA models with many time points.

4.2.4 Conclusion

In this section, another type of latent variable model was presented: latent class analysis. This method of analysis is tailored towards the simultaneous analysis of multiple categorical dependent variables and relates them to an underlying categorical variable.

In the case of the study of vulnerability processes, the longitudinal extensions, repeated-measures LCA and LTA, are particularly well-suited even if they are used to answer different substantive questions. In the case of repeated-measures LCA, it can be used to potentially identify whole trajectories of vulnerability based on multiple indicators. Repeated-measures LCA is a holistic approach to the analysis of vulnerability as it accounts for the entire vulnerability trajectory at once. In that respect, it is extremely similar to the combination of sequence and cluster analysis which is often used to study life course trajectories. The indicators could be used to designate when the threshold of negative consequences has been passed and can therefore be used to analyse multiple outcomes at once. The inclusion of covariates allows for comparing trajectories, and therefore differences in vulnerability, according to resources, sociodemographic characteristics, or contextual factors. However, the number of classes, in other words the number of possible types of trajectories, needs to be chosen in advance. Moreover, the researcher needs to assign names or labels to each of the classes, or types of trajectories, in relation to the observed patterns of the multiple indicators. Thus, determining which trajectories provide evidence of vulnerability and which ones don't depends on the results and is at the discretion of the researcher. This problem isn't unique to repeated-measures LCA, and indeed is also applicable to growth mixture models which can be considered as the counterpart to these models when the dependent variable(s) are continuous. Additionally, contrary to growth mixture models, no functional form of change over time, i.e. linear, or quadratic for instance, needs to be specified. However, time is treated, implicitly, as being a discrete variable rather than continuous.

LTA takes a different perspective and is not a holistic approach. It looks at transitions or changes in status between two given time points. If we relate this to Figure 3.1 in Section 3.3, repeated-measures LCA is the analysis of entire trajectories, while LTA can be thought of as modelling transitions from one part of the trajectory to another. Thus, LTA can be conceived of modelling transitions between different parts of the vulnerability process and the classes can be thought of as representing different states individuals can find themselves in, or outcomes they can experience, over time in relation to exposure to sources of stress. However, the interpretation of results from LTA can be relatively complicated and it is best used to understand vulnerability in the short-term. A variant of LTA is used in the second application in Chapter 7 to assess individual vulnerability to a decline in job quality in the aftermath of the 2008 Financial crisis. It allows for assessing transitions to more vulnerable forms of employment in relation to individual characteristics and resources in the short-term. However, the interpretation of these covariates is now conditional. Because LTA assumes a single-order Markov process, that is that the class an individual was in previously influences the class they are in at a later point in time, the covariates explain differences once this time dependency is taken into account. This last aspect will be considered in more detail in the application in Chapter 7.

4.3 A Note on Dynamic Panel Models

Dynamic panel models are an extension of regular panel models where the previous value of a dependent variable is included as an explanatory variable. This approach allows for taking into account the potential effect of individuals' previous situation on their current one. This is in contrast to distributed lag models which also include previous observations of the explanatory variables in the model. While such models, or variants have existed for a long time (Duncan 1969; Allison et al. 2017), their estimation is not particularly easy as there are three notable issues: the correlation of the error term with the predictors, in this case this principally concerns the lagged dependent variable, the *initial conditions* problem, and to a lesser extent the *incidental parameters* problem which applies when panel data models are estimated using the least-squares dummy variables (LSDV) approach. In this section, the case of dynamic models with continuous variables and possible solutions will be presented briefly for the first two problems.

The case of models with categorical dependent variables will also be presented as a similar approach is combined with latent class analysis in the second application in Chapter 7. In the categorical case, dynamic panel models can be used to identify, and distinguish between, "true" and "spurious" state dependence (Heckman 1981a). The regression coefficient for the lagged dependent variable should give an estimate of "true" state dependence. This measures the degree to which an individual's observed state in the present can be thought to be related to their previous state. "Spurious" state dependence is the issue of observing a link between the past and the present due to unobserved or omitted characteristics. Dynamic panel models with categorical dependent variables seek to disentangle "true" state dependence from "spurious" state dependence. A typical use case of dynamic panel models with categorical dependent variables is the analysis of labour force participation where the aim is to take into account state dependence as the unemployed typically are more likely to remain unemployed (Heckman 1981a, 92).

4.3.1 The Linear Case

The basic form of a dynamic panel model is (Halaby 2004, 535; Baltagi 2005, 135):

$$y_{it} = b_0 + b_1\ y_{i(t-1)} + b_2\ z_i + b_3\ x_{it} + v_{it} \tag{4.55}$$

where b_0 is the intercept, b_1 is the regression coefficient for the lagged dependent variable $y_{i(t-1)}$, b_2 is the regression coefficient for a time-constant variable z_i, b_3 is the regression coefficient for a time-varying variable x_{it}, and v_{it} is the error term. The subscript t varies between 2 and T, the total number of observed time periods, and the subscript i varies between 1 and N, the total number of observed individuals (units). The error term v_{it} can be further decomposed into an individual-specific time-constant and time-varying component (Baltagi 2005, 135):

$$v_{it} = u_i + u_{it} \tag{4.56}$$

The first problem is related to bias introduced by non-independence between the error term v_{it} and the lagged dependent variable $y_{i(t-1)}$. In Equation (4.55) we can see that y_{it} is not independent of the error term v_{it} and its two components u_i and u_{it} (135). A reformulation of Equation (4.55), through centreing or time demeaning, can eliminate the individual-specific u_i term:

$$\begin{aligned}(y_{it} - \bar{y}_{it}) &= b_0 + b_1(y_{i(t-1)} - \bar{y}_{i(t-1)}) + b_2(z_i - \bar{z}_i) + \\ &\quad b3(x_{it} - \bar{x}_{it}) + (u_i - \bar{u_i}) + (u_{it} - \bar{u}_{it}) \\ &= b_0 + b_1(y_{i(t-1)} - \bar{y}_{i(t-1)}) + b3(x_{it} - \bar{x}_{it}) + (u_{it} - \bar{u}_{it})\end{aligned} \tag{4.57}$$

As $u_i = \bar{u}_i$ the difference between the two comes to zero. The side-effect is that time-constant variables z_i are also eliminated as $z_i = \bar{z}_i$. Thus bias related to time-constant unobserved heterogeneity can be avoided, but this is not the case for time-varying unobserved heterogeneity i.e. the u_{it} term. This also solves the incidental parameter problem as the time-constant individual-specific term u_i no longer needs to be estimated for each individual.

This bias is shown by Nickell (1981) in the case of fixed-effects models. Nickell finds that the bias in the estimation of the b_1 coefficient in Equation (4.55) is directly related to the number of observations T and the number of observations N available. The bias approaches zero when $T \to \infty$ and $N \to \infty$ but can be substantial in the case where T is small as is the case in most longitudinal studies. Nickell (1981, 1422–1423) show that if b_0's true value were 0.5, using a panel with $T = 10$ with $N \to \infty$ would give a bias of -0.167 which is fairly large and would be even greater with a smaller T. Moreover, this bias is accentuated when covariates are included (Nickell 1981, 1424; Halaby 2004, 538).

The most used solution currently to deal with the issues of non-independence is the instrumental variable (IV) type solution (Anderson and Hsiao 1981) such as the Arellano-Bond estimator (Arellano and Bond 1991). The idea behind such approaches is to replace the $y_{i(t-1)}$ term with another variable that is uncorrelated with u_{it} but that is correlated with $y_{i(t-1)}$. The methods proposed by Anderson and Hsiao (1981) and Arellano and Bond (1991) take the same approach; the difference is the estimator used: standard IV regression in the first case and generalized method of moments (GMM) in the second. The solution is to eliminate the time-constant individual-specific error term u_i using first differencing:

$$(y_{it} - y_{i(t-1)}) = b0 + b1(y_{i(t-1)} - y_{i(t-2)}) + b3(x_{it} - x_{i(t-1)}) + (u_{it} - u_{i(t-1)}) \quad (4.58)$$

As $(y_{i(t-1)} - y_{i(t-2)})$ is correlated with $u_{i(t-1)}$, using an instrumental variable correlated with $(y_{i(t-1)} - y_{i(t-2)})$ but not with $u_{i(t-1)}$ would attenuate the bias. Anderson and Hsiao (1981), and Arellano and Bond (1991) show that $y_{i(t-2)}$ is a valid instrument as it is uncorrelated with either u_{it} and $u_{i(t-1)}$ and it is correlated with $(y_{i(t-1)} - y_{i(t-2)})$ (Anderson and Hsiao 1981; Arellano and Bond 1991; Halaby 2004, 540; Baltagi 2005, 137). One fundamental assumption is that the time-varying error terms are not serially correlated.

More recently, Moral-Benito (2013), Allison et al. (2017), and Moral-Benito et al. (2019) advocate using maximum likelihood estimators directly rather than using transformations and IV techniques. The solution is to estimate models that allow the lagged dependent variable $y_{i(t-1)}$ to be correlated with the error terms eliminating the need for first-differencing. This approach can be readily and relatively easily estimated using structural equation modelling software.

4.3.2 The Categorical Case

The differencing approaches and maximum likelihood approaches presented in the previous section do not apply to panel models where the dependent variable is noncontinuous (Wooldridge 2005; Baltagi 2005, 209). Wooldridge (2005) proposes a “simple solution” to the initial conditions problem for binary dependent variables that is more flexible, that doesn’t require defining new estimators, and that can be easily implemented unlike previous solutions such as those proposed by Heckman (1981a, 1981b), Chamberlain (1985), and Honoré and Kyriazidou (2000).

Following Wooldridge (2010, 625), a simply dynamic model with a binary dependent variable can be expressed as:

$$P(y_{it} = 1 | y_{i(t-1)}, \ldots, y_{i0}, \boldsymbol{z}_i, c_i) = G(\boldsymbol{z}_{it}\boldsymbol{\delta} + \rho y_{i(t-1)} + c_i) \quad (4.59)$$

or alternatively as a latent variable model:

$$y^*_{it} = \boldsymbol{z}_{it}\boldsymbol{\delta} + \rho y_{i(t-1)} + c_i + \epsilon_{it} \quad (4.60a)$$

with

$$y_{it} = \begin{cases} y_{it} = 1 \text{ if } y^*_{it} > \tau = 0 \\ y_{it} = 0 \text{ if } y^*_{it} \leq \tau = 0 \end{cases} \quad (4.60b)$$

and $t = 1 \ldots T$.

Here, $\boldsymbol{z}$ is the vector of time-varying covariates, y_{i0} is the initial observations of the dependent variable y, c_i is the term containing individual unobserved heterogeneity, $\boldsymbol{\delta}$ is the vector of regression coefficients for $\boldsymbol{z}$ and ρ is the regression coefficient for the lagged dependent variable. G is a link function relating the expected latent variable to y which can either be the probit or logit function. According to this specification, the $\boldsymbol{z}_{it}$ variables are assumed to be exogenous conditional on the c_i term for unobserved heterogeneity. The main difficulty is the estimation of the c_i term as it is not independent from the y_{i0}. The problem of initial conditions is then that the observed initial value of y_{i0} is *not* independent of c_i but also depends on the value of $y_{i(0-1)}$ which isn't observed either unless y_{i0} corresponds to the beginning of the process.

If the process being modelled has been observed since the beginning, there is no initial conditions problem, but this is rarely the case with panel studies. In the case of employment trajectories for instance, if everyone in a study had been observed since their first entry into the labour market, there would be no initial conditions problem as the observed y_{i0} would be the true y_{i0}. However, in most panel studies, we observe individuals at different places in the process being modelled and thus we don't observe individuals' *true* initial status. But, the more observations there are, that is $T \to \infty$, the smaller the bias related to the initial conditions is (Hsiao 2014, 253–254; Skrondal and Rabe-Hesketh 2014, 217). However, in most panel data sets, this is not feasible and therefore models taking into account the initial conditions need to be estimated.

The approach proposed by Wooldridge (2005) to estimate c_i while taking into account the fact that c_i and y_{i0} are not independent is to specify an additional model relating c_i to y_{i0}. Wooldridge (2005) proposes the following model:

$$c_i = \psi + \zeta_0 y_{i0} + \boldsymbol{z}_i \boldsymbol{\zeta} + a_i \tag{4.61}$$

where ψ is a constant, y_{i0} is the initial observation of y for an individual, ζ_0 is the associated regression coefficient, $\boldsymbol{z}_i$ are the time-varying variables at each time point except the initial time point $t = 0$ i.e. $\boldsymbol{z_i} = (\boldsymbol{z}'_{i1} \dots \boldsymbol{z}'_{iT})'$. $\boldsymbol{\zeta}$ are the associated regression coefficients for $\boldsymbol{z_i}$ and a_i is an individual-specific error. We can substitute Equation (4.61) into Equation (4.60a) giving:

$$y^*_{it} = \boldsymbol{z}_{it}\boldsymbol{\delta} + \rho y_{i(t-1)} + \psi + \zeta_0 y_{i0} + \boldsymbol{z}_i \boldsymbol{\zeta} + a_i + \epsilon_{it} \tag{4.62}$$

This model can be estimated as random-effects logit or probit model (Wooldridge 2005; Skrondal and Rabe-Hesketh 2014) and requires adding y_{i0} as an additional covariate as well as each z_{it} as an individual covariate. One disadvantage of this approach is that in the case of unbalanced panel data, i.e. when there are gaps in the observations, dealing with missing data is not necessarily straightforward as dealing with missing information on the covariates requires extra methods such a multiple imputation. Rabe-Hesketh and Skrondal (2013) propose an alternative specification for the auxiliary model estimating c_i:

$$c_i = \psi + \zeta_0 y_{i0} + \bar{\boldsymbol{z}}'_i \boldsymbol{\zeta} + \boldsymbol{z}'_{i1} \boldsymbol{\zeta}_1 + a_i \tag{4.63}$$

Rather than taking into account the non-independence of c_i and the covariates $\boldsymbol{z}$ by including $\boldsymbol{z}_i$ for each time point, this auxiliary model includes the means for each covariate, $\bar{z}_i$, as well as the covariates observed at $t = 1$, $\boldsymbol{z}'_{i1}$. This dynamic panel model can also be extended to include time-invariant covariates by incorporating them into either Equation (4.61) or Equation (4.63) which allows for controlling for some time-constant observed heterogeneity (Wooldridge 2005, 51). This specification of dynamic panel model, which corresponds to a first-order Markov process, performs better than a “naive” approach which doesn’t take into account the initial conditions problem, nor unobserved heterogeneity. The “naive” approach is, for instance, commonly used to estimate the transition models in latent transition analysis or Markov models (Skrondal and Rabe-Hesketh 2014).

However, estimating dynamic panel models using random-effects models to deal with the incidental parameter problem does have a disadvantage in that the assumption of exogeneity of covariates on unobserved heterogeneity are stronger than in the case of fixed-effects or first-difference models used to estimate dynamic panel models in the linear case. Nevertheless, this method remains a potential improvement over a naive approach which would ignore such issues in the estimation.

4.3.3 Conclusion

The principals behind dynamic panel models, namely the idea that the observed outcome in a previous point in time can influence the outcome in the present, are not exclusive to the dynamic panel models presented here. Auto-regressive latent trajectory models as discussed in Section 4.1.5 for instance are a specific type of dynamic panel model. Latent transition analysis are also an example of a dynamic panel model with a latent dependent variable. The difference is that the econometric models presented here focus more on issues related to dealing with the assumptions and problems raised by the inclusion of a lagged dependent variable.

From a more substantive point in the study of vulnerability, dynamic panel models allow for adopting a potentially more dynamic view of the process as individual trajectories are considered to be not only dependent on individuals’ resources. It allows for a more encompassing view by taking into account the dynamic nature of processes as past experiences in the process of vulnerability are a potentially important factor in determining its future progress.

In this thesis, dynamic panel models are combined with latent class analysis in Chapter 7 to analyse vulnerable employment in the aftermath of the financial crisis with the aim of understanding whether the crisis changed the relationship between individuals’ resources, but also their previous employment situations, and their current state of employment.

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Chapter 5 Mediation in Regression Models with Noncontinuous Outcomes

Testing for mediation allows for researchers to establish the degree to which an association between two variables can be explained by an indirect relationship through a third variable. For instance, when analysing the association between education and the risk of unemployment, we may be interested in the extent to which this association can be explained by the influence of education on individuals' job position which in turn would influence the risk of unemployment. Using linear regression, the degree to which job position explains the association between education and the risk of unemployment, i.e. mediates the association, can be assessed by comparing the regression coefficient for education in model excluding job position to the regression coefficient for education in a model which includes job position (Breen et al. 2013, 165). However, simply comparing regression coefficients between different nested models, as is possible in the case of linear regression models, isn't sufficient to fully assess the mediating effect of additional variables in model with noncontinuous outcomes. This so-called "naive" approach will often tend to understate the magnitude of mediation (VanderWeele 2016). This is due to the non-independence of the residual error term in regression models with noncontinuous outcomes.

Previous methods such as "Y-standardization" (Winship and Mare 1984; Long 1997), or the use of average partial effects (Wooldridge 2010; Mood 2010) have been proposed but they do not fully correct the problem. A more recent approach proposed by Karlson et al. (2012), known as the KHB method (see also Karlson and Holm 2011; Breen et al. 2013, 2018a, 2018b), has been demonstrated to rescale the coefficients of nested regression models with noncontinuous dependent variables allowing them to be directly compared, and consequently permit the application of standard mediation testing techniques. In this chapter, mediation in the case of regression models with noncontinuous outcomes will be discussed and the different methods will be compared. An implementation of the KHB method in R will also be discussed, and an application will later be demonstrated comparing the results of this package with the Stata implementation of the KHB method (Kohler et al. 2011).

5.1 A Brief Refresher on Mediation in Regression Models

The most common approach used for the formal study of mediation in regression models is that of Baron and Kenny (1986) (see also Judd and Kenny 1981; Preacher 2015; VanderWeele 2015, 2016; Hayes 2018). Their approach proposes testing mediation in four steps. In the first, a regression model is estimated with only the main explanatory variable(s). Then, a regression model is estimated where the mediator(s) are regressed on the main explanatory variable(s). The third step is to regress the mediator(s) on the dependent variable, and finally the fourth step is to estimate a combined model with the dependent variable regressed on the explanatory variable(s) and moderator(s). These steps can be summarized in Figures 5.1 and 5.2.

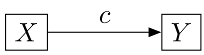

Figure 5.1 – Regression model with no mediators

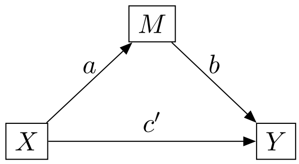

Figure 5.2 – A simple mediation model

Figure 5.1 shows what is estimated in the first step i.e. the relationship between an explanatory variable X (or more than one) and the dependent variable Y. This corresponds to path c. Figure 5.2 shows what is estimated in steps two through four. In step two, the relationship between the mediator and the explanatory variable is estimated. This corresponds to path a. In step three, the relationship between the mediator M and dependent variable Y is estimated. This corresponds to path b. The final step, estimating the relationship between X and Y while taking into account M, is given by path c'.

In a linear model, the degree of mediation is given by the difference in strength of the association between the main explanatory variable X and the dependent variable Y when the mediator isn't included and when the mediator is included i.e. $c - c'$. This difference can also be expressed as the product of paths a and b and thus we obtain the following equality:

$$ab = c - c' \tag{5.1}$$

These two manners in determining the extent of mediation, using the difference $c - c'$ or the product ab, are respectively referred to as the "difference method" and the "product method".

As for the concrete manner in which to estimate the paths, the generally accepted approach is either to estimate all the equations simultaneously using structural equation modelling, or to estimate three regression models. The first regression model simply corresponds to Figure 5.2 and is a regression of Y on X. The second regression model estimates path a by regressing M on X. The final regression model estimates both paths b and c' by regressing Y on X and M. It is also possible to omit the first step, i.e. Figure 5.1, and only estimate the models necessary for estimating the paths in Figure 5.2 as it is possible to recover the coefficient for path c from c', a, and b.

This manner of analysing mediation can be extended to multiple explanatory, or "key", variables as well as to multiple mediators. In the case of a single key X variable and multiple M mediators, steps two through four correspond to Figure 5.3.

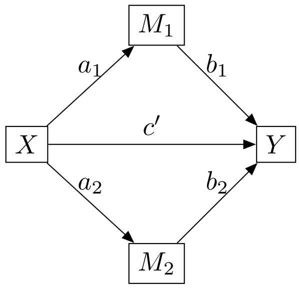

Figure 5.3 – A model with multiple mediators

The relationship $c - c'$ still holds, but the product method now corresponds to $\sum_{i=1}^{N} a_i b_i$. In other words, when there are multiple mediators, the relationship in Equation (5.1) becomes:

$$\sum_{i=1}^{N} a_i b_i = c - c' \tag{5.2}$$

In the case of multiple explanatory or X variables, a distinction needs to be made between variables that are really considered explanatory, and confounding/control variables. In the case of multiple explanatory variables and a single mediator, step one corresponds to Figure 5.4 and steps two through four correspond to Figure 5.5. In this situation the relationship between the difference in coefficients and the

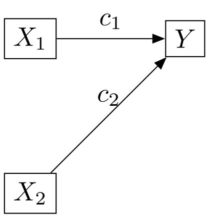

Figure 5.4 – A model with multiple explanatory variables

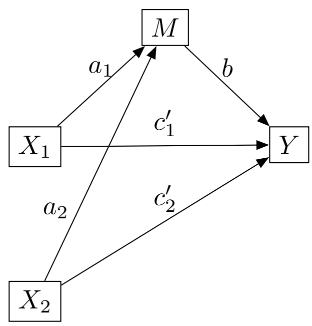

Figure 5.5 – A mediation model with multiple explanatory variables

product as expressed in Equation (5.1) becomes:

$$ba_i = c_i - c'_i \tag{5.3}$$

Another variant of the mediation model is one that includes control variables or confounders. Compared to a simple mediation model, Figures 5.1 and 5.2, the model now includes two control variables C_1 and C_2 in all four steps as shown in Figures 5.6 and 5.7. However the relationship between the difference in coefficients and the product as expressed in Equation (5.1) remains the same. The difference

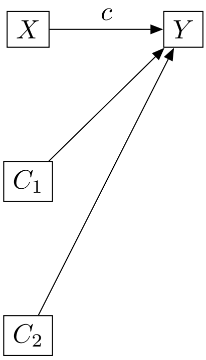

Figure 5.6 – A model with multiple control variables

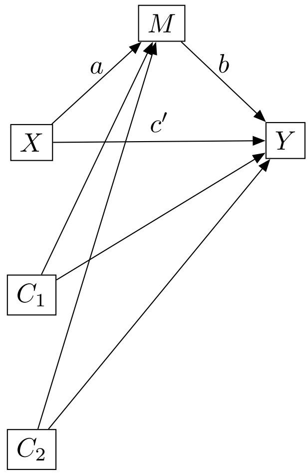

Figure 5.7 – A mediation model with multiple control variables

is related to the interpretation of the paths. The mediation can be considered as a conditional one i.e. mediation in the case where the control variables C_1 and C_2 are held constant (Hayes 2018, 124).

It is possible to combine the specific cases presented in Figures 5.1 through 5.7 to estimate a mediation model with multiple mediators, control variables/confounders, and explanatory variables. It is also possible to further expand these models to include moderators and thus estimate moderated-mediation, where a variable modifies the influence of the mediator.

After estimating the mediation effect, it is possible to test whether the mediation is statistically different from zero. The most popular method for testing mediation until recently was the Sobel test (Sobel 1982). The standard error for the product ab is derived from the more general Delta method for estimating variances or other moments (Oehlert 1992). The (first-order) Sobel estimate of the standard error of a mediation by a mediator variable M_i, that is the product of paths a_i and b_i entering and leaving the mediator respectively, by the following formula (MacKinnon et al. 2002):

$$\mathrm{se}_{a_i b_i} = \sqrt{a_i^2 se_{b_i}^2 + b_i^2 se_{a_i}^2} \tag{5.4}$$

A more accurate second order estimate (Aroian 1947; MacKinnon et al. 2002; Hayes 2018, 162) is:

$$\mathrm{se}_{a_i b_i} = \sqrt{a_i^2 se_{b_i}^2 + b_i^2 se_{a_i}^2 + se_{a_i}^2 se_{b_i}^2} \tag{5.5}$$

There is also a multivariate extension (Sobel 1986, 1987; Bollen 1989, 390–393) to test the contribution of multiple mediators to the overall mediation $c - c'$. However, it requires potentially complex – the complexity depends on the complexity of the model – matrix algebra to compute the necessary derivatives and the covariance matrix to be able to obtain the standard error with:

$$\sqrt{\boldsymbol{a}'\boldsymbol{\Sigma}\boldsymbol{a}} \tag{5.6}$$

where $\boldsymbol{a}$ contains the partial derivatives with respect to the parameters computing the mediation effect and $\boldsymbol{\Sigma}$ is the associated variance-covariance matrix.

However, the delta method is an asymptotic one. In other words, the variance, or standard error, approximates the population value better the larger the sample. The estimator of the indirect effects is also assumed to be approximately normally distributed. Moreover, the delta method has its own assumptions relative to the derivations that allow for estimating the variance (whether the function is differentiable, etc.). In addition, tests derived from the delta method, more specifically the Sobel test, are considered to have low power not only when the sample size is small but also when mediation effects are not large.

More recently, nonparametric bootstrap-based tests have been advocated as a more flexible and more general manner for testing mediation (Bollen and Stine 1990; Preacher and Hayes 2004, 2008; Hayes 2018; Breen et al. 2018a). The main advantage of using bootstrap, or resampling, methods to test mediation effects is that it requires fewer distributional assumptions be made concerning the estimator of the mediation effects. It is also more suited to use in cases where sample sizes are small as variances estimated using the delta method are asymptotic. Moreover, it can be used to estimate standard errors for other arbitrary ratios, or differences without requiring the derivation of new analytic expressions (Breen et al. 2018a, 6).

While all of this applies to regression models with a continuous outcome variable, the equalities defined in Equations (5.1) through (5.3) do not hold when the dependent variable is noncontinuous. For example, in the case of logistic regression, the difference in the coefficients for the paths c and c' in the simplest mediation model, a single mediator and a single explanatory variable as in Equation (5.1), is not equal to the product of the coefficients for paths a and b. Thus, to test mediation with a noncontinuous dependent variable, extra steps need to be taken in order to ensure this equality. Different ways to solve this problem, or at least attenuate it, will be presented in the next section with a focus on the KHB method proposed in Karlson et al. (2012) and its reformulation in Breen et al. (2018a).

5.2 Comparing Coefficients between Regression Models with Noncontinuous Outcomes

The problem with comparing coefficients between nested models with noncontinuous outcomes, and also the reason the relationship $ab = c - c'$ doesn't hold, is due to the nature the residual variance term in noncontinuous regression models. In linear regressions, the residual variance follows a normal distribution $N(0, \sigma^2)$ where σ^2 is not fixed. However, this is not the case for regressions with noncontinuous outcomes.

We can express a logistic regression model as a latent variable model (Mood 2010; Breen et al. 2013, 2018b), similarly to what is done in the case of structural equation modelling (see Section 4.1.1 in particular page 83). Suppose we have two logistic regression models as defined in Equations 5.7a and 5.7b with the reduced model in Equation 5.7a being nested within the full model in Equation 5.7b.

$$y_i^* = \alpha_R + \beta_{1R}\, x_{1i} + \epsilon_{iR} \tag{5.7a}$$

$$y_i^* = \alpha_F + \beta_{1F}\, x_{1i} + \beta_{2F}\, x_{2i} + \epsilon_{iF} \tag{5.7b}$$

y_i^* is the unobserved latent dependent variable, α_R and α_F are the intercepts in the reduced and full models respectively, β_{1R} and β_{1F} are the regression coefficients for predictor x_1 in the reduced and full models, β_{2F} is the regression coefficient for predictor x_2 in the full model, and ϵ_{iR} and ϵ_{iF} are the random error terms in the full and reduced models.

However y^* is unobserved; we only observe y which in the binary case only takes a value of 1 or 0. We can, however, establish a relationship between y and y^* as follows:

$$\begin{cases} y = 1 \text{ if } y^* > \tau \\ y = 0 \text{ if } y^* \leq \tau \end{cases} \tag{5.8}$$

where τ is a threshold, or value, on the latent scale above which we observe $y = 1$. In the binary case, the threshold τ is typically set to 0.

In non-linear probability models such as logistic or probit regression, the aim is to predict the probability of observing $y = 1$ or equivalently the probability of $y^* > \tau$ which in the binary case is $y^* > 0$.

In order to create a linear relationship between the observed dependent variable y and the independent variables x_1 and x_2 it is possible to use a transformation such as the logit transformation.

If we apply the logit transformation to the reduced and full models in Equations (5.7a) and (5.7b) we get:

$$\ln\left(\frac{p}{1-p}\right) = a_R + b_{1R}\, x_{1i} \tag{5.9a}$$

$$\ln\left(\frac{p}{1-p}\right) = a_F + b_{1F}\, x_{1i} + b_{2F}\, x_{2i} \tag{5.9b}$$

where p is $\Pr(y = 1) = \Pr(y^* > \tau)$, a_R and a_F are the intercepts in the logistic regression for the reduced and full models, b_{1R} and b_{1F} are the logistic regression coefficients for predictor x_1 in the reduced and full models, b_{2F} is the logistic regression coefficient for predictor x_2 in the full model. These terms are not equal to those in Equations (5.7a) and (5.7b) as will be shown below. In Equations (5.9a) and (5.9b) no error terms are displayed because they have a fixed variance of $\pi^2/3$ in the case of a logistic regression or 1 in the case of a probit regression.

To draw the link between Equations (5.7) and Equations (5.9) let us respecify Equations (5.7a) and (5.7b):

$$y_i^* = \alpha_R + \beta_{1R}\, x_{1i} + \sigma_R w_R \tag{5.10a}$$

$$y_i^* = \alpha_F + \beta_{1F}\, x_{1i} + \beta_{2F}\, x_{2i} + \sigma_F w_F \tag{5.10b}$$

The "true" random error terms ϵ_{iR} and ϵ_{iF} for the reduced and full models can be expressed as the product of a scaling factor – σ_R and σ_F for the reduced and full models – and a random variable – w_R and w_F for the reduced and full models – following a logistic distribution with a mean of 0 and a variance of $\pi^2/3$ since we have logit models for Equations (5.9). w_R and w_F could also follow a normal distribution with a mean of 0 and a variance of 1 if we used probit models in Equations (5.9). The scale parameters allow for recovering the "true" variance of ϵ_{iR} and ϵ_{iF} in the underlying latent models. Doing this allows us to more easily show the relationship between the coefficients in the latent models in Equations (5.7) and those that are estimated with the models in Equations (5.9).

Karlson et al. (2012) and Breen et al. (2013) show that we can express $P(y = 1)$ in the binary case as $P(y^* > 0)$. Further they show (see also Wooldridge 2010, 583) that in the case of the reduced model in Equation (5.7b), we can express this probability as:

$$\begin{aligned} p = P(y^* > 0) &= P\left(\epsilon_{iR} > -\frac{\alpha_R}{\sigma_R} - \frac{\beta_{1R}}{\sigma_R}x_{1i}\right) \\ &= \frac{\exp\left(\frac{\alpha_R}{\sigma_R} + \frac{\beta_{1R}}{\sigma_R}x_{1i}\right)}{1 + \exp\left(\frac{\alpha_R}{\sigma_R} + \frac{\beta_{1R}}{\sigma_R}x_{1i}\right)} \end{aligned} \tag{5.11}$$

If we substitute this expression into $\ln(p/(1-p))$ we obtain:

$$\ln\left(\frac{p}{1-p}\right) = \frac{\alpha_R}{\sigma_R} + \frac{\beta_{1R}}{\sigma_R}x_{1i} \tag{5.12}$$

and analogously for the full model we obtain:

$$\ln\left(\frac{p}{1-p}\right) = \frac{\alpha_F}{\sigma_F} + \frac{\beta_{1F}}{\sigma_F}x_{1i} + \frac{\beta_{2F}}{\sigma_F}x_{2i} \tag{5.13}$$

This shows that the parameters estimated in Equations (5.9a) and (5.9b) are *scaled* and do not directly estimate the underlying regression coefficients from the latent variable models. Furthermore, this means that when comparing coefficients from two different non-linear probability models, we are comparing coefficients that are on different scales.

Now let's take the case where x_2 is an omitted variable and is correlated with x_1. Following Mood (2010), we can express this relationship as follows:

$$x_{2i} = \gamma_0 + \gamma_1 x_{1i} + v_i \tag{5.14}$$

Equation (5.14) expresses the relationship between the two variables as a linear regression with γ_0 being the intercept, γ_1 the regression coefficient corresponding to the effect of x_1, and v_i the error term. Substituting this expression into Equation (5.13), we find that the effect of x_1 is not just β_{1F} but $\beta_{1F} + \beta_{2F}\gamma_1$. This is also the case in linear regression.

However, in the case of noncontinuous outcomes, the omission of a variable also introduces a problem related to differences in scaling. Let's assume that the scaling factor σ_F in Equation (5.13) is $\sqrt{3.29}/\sqrt{3.29} = \sqrt{\pi^2/3}/\sqrt{\pi^2/3}$ and that therefore the true variance is the same as the assumed variance. If we omit x_2 from Equation (5.13), the residual variance increases as the error term also includes the residual variance v_i from Equation (5.14) and the true residual variance is $\mathrm{var}(\epsilon_R) + \beta_{2F}^2 \mathrm{var}(v)$. The scaling factor σ_R subsequently becomes:

$$\sigma_R = \frac{\sqrt{3.29 + \beta_{2F}^2 \mathrm{var}(v)}}{\sqrt{3.29}}$$

Therefore, we find that the scaling factors in Equations (5.12) and (5.13) are not the same.

Consequently, in the case of mediation, the relationship $c - c' = ab$ no longer holds because c and b, which are estimated in the same model, and c', which isn't, are not measured on the same scale. In the case of Equations (5.9) and (5.14), $c = b_{1R}$, $c' = b_{1F}$, $a = \gamma_1$, and $b = b_{2F}$.

If we take Equations (5.7a), (5.7b) and (5.14), the difference between the coefficients β_{1R} in Equation (5.7a) and β_{1F} (5.7b) is equivalent to γ_1 from Equation (5.14) multiplied by β_2 *in the latent models* which we do not observe. Thus in the case of the latent models the relationship:

$$\beta_{1R} - \beta_{1F} = \gamma_1 \beta_{2F} \tag{5.15}$$

holds.

However, since we only observe b_{1R}, b_{1F} and b_{2F} from Equations (5.9a) and (5.9b) this gives us:

$$\frac{\beta_{1R}}{\sigma_R} - \frac{\beta_{1F}}{\sigma_F} \neq \gamma_1 \frac{\beta_{2F}}{\sigma_F} \tag{5.16}$$

due to the different scaling factors. For the relationship to hold, the scaling factors σ_R and σ_F would have to be the same.

5.3 Solving the Issue of Differences in Scaling

To be able to compare coefficients between two different models with noncontinuous outcomes, the scaling factor between the two models needs to be made equivalent in some manner. The literature proposes, three different solutions for the issue of differences in scaling between different models with noncontinuous outcomes: "Y-standardization" (Winship and Mare 1984; Long 1997, 69–70), the use of average partial effects (APE) (Wooldridge 2010, 577–579; Mood 2010), and the KHB method (Karlson et al. 2012; Karlson and Holm 2011; Breen et al. 2013, 2018a, 2018b).

5.3.1 Y-Standardization

One solution to this problem of differences in scale is proposed by Winship and Mare (1984). Their method to deal with the fixed of the variance of the distribution of the residuals in the case of noncontinuous outcomes is to divide the regression coefficients by the standard deviation of the unobserved, latent, dependent variable

y^*. While they present their solution in the context of latent variable models estimated in the SEM framework, this can also be achieved in the standard regression modelling framework for binary variables.

Long (1997, 69–70) shows that it is possible to estimate the variance of the underlying latent variable y^* with:

$$\widehat{\mathrm{Var}}(y^*) = \widehat{\boldsymbol{\beta}}'\mathrm{Var}(\boldsymbol{x})\widehat{\boldsymbol{\beta}} + \mathrm{Var}(w) \tag{5.17}$$

where $\widehat{\boldsymbol{\beta}}$ is the vector containing the estimates of the regression coefficients that is, for example, $\hat{a}_R$ and $\hat{b}_{1R}$ in Equation (5.9a). $\mathrm{Var}(w)$ is the fixed residual variance of the distribution chosen for the residual error term which is equal to $\frac{\pi^2}{3}$ in the case of logistic regression or 1 in the case of probit regression. $\widehat{\mathrm{Var}}(\boldsymbol{x})$ is the covariance matrix of the independent variables $\boldsymbol{x}$. From this expression, we can see that the variance of the underlying latent variable y^* is composed of the fixed residual variance and the variance related to the independent variables. What this expression also shows us is that unlike linear regression, the addition of variables increases the explained variance of y^*, but *doesn't* decrease the unexplained part $\mathrm{Var}(w)$. Once the variance of y^* is approximated, the "y-standardized" coefficient is:

$$\frac{\hat{b}}{\sqrt{\widehat{\mathrm{Var}}(y^*)}} \tag{5.18}$$

where b is the estimated regression coefficient from a logistic or probit regression for instance.

5.3.2 Average Partial Effects

Another option is to use average partial effects (APE) to compare effects between different noncontinuous regression models. Formally, APEs are (Wooldridge 2010, 577):

$$\mathrm{APE}_j = \widehat{\beta}_j \frac{1}{N} \sum_{i=1}^{N} g\left(\boldsymbol{x}_i \widehat{\boldsymbol{\beta}}\right) \tag{5.19}$$

$\widehat{\beta}_j$ is the estimate of the coefficient of a variable of interest j. $\boldsymbol{x}_i$ is the data or values for the independent variables for an individual i in the sample, N is the sample size and $\widehat{\boldsymbol{\beta}}$ are the estimated regression coefficients. g is the derivative of function G which links the linear predictor to the (predicted) probability i.e. the link function (Wooldridge 2010; Mood 2010; Karlson et al. 2012). In the case of a logistic regression, G corresponds to:

$$\frac{e^{\boldsymbol{x}\boldsymbol{\beta}}}{1 + e^{\boldsymbol{x}\boldsymbol{\beta}}} = p \tag{5.20}$$

which is the logistic cumulative density function, and g is:

$$\frac{e^{\boldsymbol{x}\boldsymbol{\beta}}}{\left(1 + e^{\boldsymbol{x}\boldsymbol{\beta}}\right)^2} = p(1-p) \tag{5.21}$$

The same procedure is also applicable to distributions other than the logistic distribution. Wooldridge (2010) shows that APEs provide similar results to the coefficients of a linear probability model i.e. a regression in which a binary dependent variable is treated as continuous. Consequently, the interpretation of the APE of a specific variable is similar to the way in which a regression coefficient would be interpreted in a linear model. Thus, the APE of the specific variable x_j expresses how much the probability of observing a specific outcome would increase or decrease for a 1-unit change in x_j in the population because it is an *average* effect. In a sense, APEs "standardize" regression coefficients by putting them on the same scale by relating them to the probability of observing an outcome.

5.3.3 KHB Method

The KHB method proposed by Karlson et al. (2012) takes another approach to rescaling regression coefficients. If we recall that the scaling factors vary between different regression models with categorical dependent variables, the approach taken by Karlson et al. is to recover the scaling parameter from the more complete model in the reduced model, that is to make $\sigma_R \approx \sigma_F$. Their proposed solution is to *residualize* the contribution of additional variables that do not appear in the reduced model. The residualized variables are obtained by estimating a linear regression of the additional variables not present in the reduced model – x_2 – on the variables present in the reduced model – x_1. This corresponds to estimating the model in Equation (5.14) and substituting x_2 in the full model with the residuals obtained from Equation (5.14) which corresponds to:

$$\tilde{z}_{2i} = x_{2i} - \gamma_0 + \gamma_1 x_{1i} \tag{5.22}$$

where γ_0 and γ_1 are the coefficients from a linear regression of x_2 on x_1, as in Equation (5.14), and $\tilde{z}_{2i}$ are the residuals or the *residualized* contribution of x_2.

So, instead of comparing the coefficients between Equation (5.9a) and (5.9b) directly – the so-called "naive" method – another model is estimated using the residualized additional variables instead of the reduced model in Equation (5.9a). This model is:

$$\ln\left(\frac{p}{1-p}\right) = a_{F^*} + b_{1F^*}\ x_{1i} + b_{zF^*}\ \tilde{z}_{2i} \tag{5.23}$$

which corresponds to the following latent model:

$$y_i^* = \alpha_{F^*} + x_{1i}\beta_{1F^*} + \tilde{z}_{2i}\beta_{zF^*} + \sigma_{F^*}w_{F^*} \tag{5.24}$$

The logic behind using the residual contribution is to remove the common variance between variables x_1 and x_2 in explaining y. Consequently the residualized variable $\tilde{z}_2$ should be completely uncorrelated with x_1. By definition then, the regression coefficient β_{1F^*} in Equation (5.24) when $\tilde{z}_{2i}$ is included should be the same as if the residualized variable were not included i.e. β_{1R} in Equation (5.7a) is the same as β_{1F^*} in Equation (5.24). However, the other consequence of including the residualized variable $\tilde{z}_2$ is that it allows for re-parameterizing the reduced model and gives us b_{1F^*}/σ_{F^*} rather than b_{1R}/σ_R with $\sigma_{F^*} = \sigma_F$.

The advantage of the KHB method over "Y-standardization" and the average partial effects approach is that it is a re-parameterization of the full model. This means that the residual variance will be the same in both models which is not true with other methods as they use the estimates from Equation (5.9a) and thus the scale terms of the underlying latent models are not equal; $\sigma_R \neq \sigma_F$. As the scaled coefficients from Equations (5.23) and (5.9b) are now on the same scale, the mediation difference equality holds meaning that the difference in coefficients or the product of the paths gives a scaled difference in the underlying latent coefficients which quantifies the mediating or confounding effect of x_2.

Because b_{1F} and b_{1F^*} are now scaled by the same factor in Equations (5.9b) and (5.24), we find that if we take the ratio of the two coefficients (confounding ratio), we obtain the same ratio as with the true underlying coefficients from the unobserved latent parameters:

$$\frac{b_{1F}}{b_{1F^*}} = \frac{\frac{\beta_{1F}}{\sigma_F}}{\frac{\beta_{1F^*}}{\sigma_{F^*}}} = \frac{\frac{\beta_{1F}}{\sigma_F}}{\frac{\beta_{1R}}{\sigma_F}} = \frac{\beta_{1F}}{\beta_{1R}} \tag{5.25}$$

It is also possible to calculate the magnitude of rescaling between the reduced and full models:

$$\frac{b_{1F*}}{b_{1R}} = \frac{\frac{\beta_{1F*}}{\sigma_{F*}}}{\frac{\beta_{1R}}{\sigma_R}} = \frac{\sigma_R}{\sigma_F} \tag{5.26}$$

A reformulation of this method is proposed by Breen et al. (2018a). Rather than calculate the residualized confounding variables, it proposes another approach using the predicted values of the dependent variable on the latent scale, that is the predicted logit values. In this approach, the dependent variable is calculated using the predicted logit values V for each observation:

$$V_i = a + x_{1i}b_1 + x_{2i}b_2 \tag{5.27}$$

Then the reduced model excluding x_2 and the full model including x_2 are estimated using linear regression:

$$V_i = a_{vR} + x_{1i} \times b_{1vR} + \epsilon_{ivR} \tag{5.28a}$$

$$V_i = a_{vF} + x_{1i} \times b_{1vF} + x_{2i} \times b_{2vF} \tag{5.28b}$$

There is no error term in Equation (5.28b) as the model is saturated. Breen et al. show that the ratio of b_{1vF}/b_{1vR} is the same as the ratio in Equation (5.25). Because the estimated coefficients now come from linear regressions, the following relationship holds:

$$b_{1vR} = b_{1vF} + b_{2vF}\frac{\mathrm{cov}(x_1, x_2)}{\mathrm{var}(x_1)} \tag{5.29}$$

It is also the case that the coefficients in Equation (5.28b) are equal to those in Equation (5.9b) as the coefficients estimated from the regression in Equation (5.28b) will be the same as the coefficients used to generate the dependent variable i.e. $b_{1vF} = b_{1F}$ and $b_{2vF} = b_{2F}$. Therefore we have:

$$\frac{b_{1F}}{b_{1F} + b_{2F}\frac{\mathrm{cov}(x_1,x_2)}{\mathrm{var}(x_1)}} = \frac{\frac{\beta_{1F}}{\sigma_F}}{\frac{1}{\sigma_F}\left(\beta_{1F}\frac{\mathrm{cov}(x_1,x_2)}{\mathrm{var}(x_1)}\right)} = \frac{\frac{\beta_{1F}}{\sigma_F}}{\frac{\beta_{1R}}{\sigma_F}} = \frac{\beta_{1F}}{\beta_{1R}} \tag{5.30}$$

Testing Mediation with the KHB Method

As for testing the mediation, Karlson et al. (2012) propose a Sobel-like test derived using the delta method. Following the generalized expression for the Sobel test in Equation (5.6) – $\sqrt{\boldsymbol{a}'\boldsymbol{\Sigma}\boldsymbol{a}}$ – Kohler et al. (2011) provide the necessary information to find $\boldsymbol{a}$ and $\boldsymbol{\Sigma}$. $\boldsymbol{a}$ is a column vector containing the partial derivatives, i.e. regression coefficients $\gamma_{\boldsymbol{X}}$, from the regressions of the mediators on the explanatory variables and the coefficients $\boldsymbol{b_Z}$ of the mediating variables from the full regression model:

$$\boldsymbol{a} = \begin{pmatrix} \gamma_{\boldsymbol{X}} \\ \boldsymbol{b_Z} \end{pmatrix} \tag{5.31}$$

The matrix $\boldsymbol{\Sigma}$ is a block diagonal matrix containing the covariance matrix $\boldsymbol{\Sigma}_{\boldsymbol{b_Z}}$ from the full regression for the $\boldsymbol{b_Z}$ coefficients and a covariance matrix $\boldsymbol{\Sigma}_{\gamma_x}$ obtained from a seemingly unrelated regression (Zellner 1962) of the mediators on the explanatory variables:

$$\begin{pmatrix} \boldsymbol{\Sigma}_{\gamma_x} & 0 & \\ 0 & \boldsymbol{\Sigma}_{\boldsymbol{b_Z}} & 0 \end{pmatrix} \tag{5.32}$$

For the reformulated method in Breen et al. (2018a), the authors recommend using nonparametric bootstrap to derive standard errors and confidence intervals. They argue that deriving an analytic expression taking into account the uncertainty of the estimated dependent variable V in combination with reusing V to estimate the parameters in Equation (5.28a) would be extremely difficult. The choice to use nonparametric bootstrap is also in line with more recent developments in mediation testing within the linear regression framework which recommend this method.

To conclude, the KHB method solves the issue of differences in scaling between regression models with noncontinuous outcomes by adjusting the full model. This adjustment via the inclusion of "residualized" variables allows for obtaining the regression coefficient of a reduced model nested within a more complete model on the same scale as the full model. An implementation of this method in R (R Core Team 2020) will now be discussed.

5.4 A Short Application

To illustrate the use of the KHB method, we will estimate a discrete-time survival model in Switzerland using time-dummies to study the chances of exiting employment. The aim is to analyse the mediating effect of contract duration on sociodemographic characteristics and their relationship with the chances of making an exit from employment after the 2008 Financial Crisis. In this section, we will compare the naive approach, where the coefficients are directly compared, to the KHB method.

This illustrative application investigates the mediating effect of a limited-duration contract on individuals' chances of exiting employment in relation to their sex using discrete-time event history analysis. Generally, female individuals are more likely to experience unemployment than males (Azmat et al. 2006; Koutentakis 2015; Bičáková 2016). However this was not the case for most Western countries during the Great Recession (Keeley and Love 2010; Hout et al. 2011; Pissarides 2013), as evidenced by Section 2.2.1. However, as will be shown in more detail in Chapter 6, Switzerland is somewhat of an exception as female unemployment followed a similar pattern to male unemployment (OFS 2018). In addition, individuals without unlimited duration contracts are generally more likely to lose employment, and this remained the case during the crisis (Giesecke and Groß 2003; Scherer 2004; Boeri and Jimeno 2016; Gebel and Giesecke 2016). Moreover, individuals of the female sex are generally more likely to be employed in less secure jobs where limited duration contracts are more common (Kalleberg 2000; Petrongolo 2004). Therefore, we could hypothesize that the relationship between individuals' sex and their likelihood of exiting unemployment can be mediated by their employment conditions.

5.4.1 Data & Methods

For this short application, 9 waves of the Swiss Household Panel covering the years 2007 to 2015 are used. We analyse individuals who in 2007 were employed and aged between 18 and 55. Two sociodemographic characteristics – age, and years of education – measured in 2007 are treated as time-constant control variables. Our main variable of interest or *key* variable, the one which is being tested for mediation, is sex. The mediator is the type of employment contract in 2007 and is a binary time-constant variable distinguishing between fixed-term and unlimited-duration contracts. The dependent variable is binary indicator which takes the value 1 if an individual became unemployed in 2008 or later, or 0 if an individual had any other labour market status (employed, out of the labour market, etc.) and never became unemployed.

To illustrate the KHB method, we estimate two discrete-time event history models using logistic regression with `glm()`. Time dummies for each year between 2008 and 2015 are included and there is no intercept. The first model includes the time dummies, two control variables – age in 2007 and years of education in 2007 – and the main explanatory variable which is individuals' sex. The second model adds contract type in order to test its mediating effect on the relationship between sex and the chances of becoming unemployed. As we are only interested in the first observed entry into unemployment, a simple logistic regression is sufficient (Allison 2014). We then compare the difference in the mediation effect when using the so-called "naive" approach where the coefficients are compared directly between models and the KHB method.

5.4.2 Results

Table 5.1 contains the results for the "naive" approach as well as the KHB method. Model 2 is the same regardless of whether the naive model or the KHB method is used as the KHB method provides coefficients for reduced models (excluding certain covariates) that are on the same scale as the full model including all covariates.

Before commenting on the mediating effect of the contract duration, let's briefly look at the results in general for Model 2. The time dummies show that the chances of becoming unemployed are relatively low. Taking the inverse logit – $1/1 + e^{-x}$

	Model 1 “Naive”	Model 1 KHB	Model 2
Age	-0.024**	-0.020**	-0.012
	(0.008)	(0.007)	(0.008)
Female (vs. male)	0.341*	0.350*	0.340*
	(0.162)	(0.162)	(0.162)
Years of education	-0.068*	-0.062*	-0.054*
	(0.028)	(0.027)	(0.027)
Limited contract			0.832***
			(0.207)
D_{2008}	-3.220***	-3.497***	-4.022***
	(0.481)	(0.471)	(0.513)
D_{2009}	-2.561***	-2.835***	-3.356***
	(0.460)	(0.449)	(0.492)
D_{2010}	-2.713***	-2.989***	-3.511***
	(0.468)	(0.458)	(0.500)
D_{2011}	-2.802***	-3.074***	-3.589***
	(0.473)	(0.464)	(0.504)
D_{2012}	-3.175***	-3.449***	-3.968***
	(0.499)	(0.490)	(0.529)
D_{2013}	-2.638***	-2.909***	-3.423***
	(0.475)	(0.466)	(0.506)
D_{2014}	-2.985***	-3.254***	-3.767***
	(0.498)	(0.489)	(0.527)
D_{2015}	-3.411***	-3.682***	-4.199***
	(0.534)	(0.526)	(0.562)
N		2,495	
N obs.		15,367	

Table 5.1 – Results of the discrete-time model with the “naive” approach. Logit estimates with standard errors in brackets.

where x is the regression coefficient – of the time dummy coefficients, we can see that, once the covariates are taken into account, the probability of becoming unemployed is 1.76% in 2008. It increases to 3.37% in 2009 before it begins to decreases again with a little rise in 2013 and 2014.

As for the covariates, in the first two models presented in Table 5.1 we see that older individuals are less likely to become unemployed than younger individuals. However the effect of age becomes non-significant when the type of employment contract is included in Model 2. In the case of education, in all three models, a higher level of education is associated with a decrease in the likelihood of entering unemployment. We also see that individuals of the female sex are more likely to become unemployed than males in all three models. Finally, in Model 2, we also find that people with limited duration contracts are more likely to experience unemployment than those with permanent contracts.

Comparing the results of the "naive" version of Model 1 to the KHB method results shows little change in the coefficients for age or years of education (though the size of the coefficients decreased when using the KHB method). There is a difference in the size of the coefficient for sex and the size of the coefficient is larger when applying the KHB method. Nevertheless, in relation to Model 2, with both methods we can see that the addition of the contract type variable reduces the size of the coefficient for sex.

If we look at the difference in coefficient for sex between Model 2 and both variants of Model 1, we find that the difference in coefficients is approximately 0.01 when using the KHB method, but only 0.001 or ten times smaller, when using the naive approach. This shows the problem of underestimating mediation effects when using the naive method. Using the method for testing mediation described in Section 5.3.3 while treating age, education, and the time dummies as controls variables, we obtain the following results:

	Est.	Std. Err.	*z*	*p*
Mediation effect	0.010	0.005	2.130	0.033
a path coef.	0.012	0.005†	2.552	0.011
b path coef.	0.832	0.207	4.011	< 0.000

Table 5.2 – Mediating effect of contract type using the product method with the KHB method
† indicates robust std. err.

The *b* path estimate corresponds to the regression coefficient for "limited contract" in Table 5.1. The *a* path coefficient is the regression coefficient, with robust standard errors, of sex from a regression of sex on contract type. This is the same variant of the mediation model as illustrated in Figure 5.7 in Section 5.1. Multiplying together the coefficients for paths *a* and *b*, 0.012×0.832, we get approximately 0.010 after rounding. This is also the same as the difference between the coefficient for sex in the full model in Table 5.1 and the reduced KHB model showing the equivalence of the product method and difference method when using the KHB method. However, the product method *doesn't* give the same results as the difference between the coefficient for sex in the full model and the coefficient for sex in the "naive" reduced model. This demonstrates that the relationship $ab = c - c'$, which is the fundamental relationship for mediation models (cf. Section 5.1), doesn't hold when not using the KHB method.

5.4.3 Summary

In summary, the application here illustrates the risks of underestimating mediation effects when simply comparing regression coefficients in order to assess mediation in the case of regression models with noncontinuous outcomes. This underlines the importance of taking into account the differences in the scaling of coefficients in nested models when making comparisons. This also demonstrates the problem related to scaling when using the product method to estimate the magnitude of the mediation effect as opposed to looking at the difference in coefficients which is not present with continuous outcomes. The KHB method provides a method for solving the issue of differences in scaling between different nested models with non-continuous outcomes. It also solves the problem of the discrepancy between assessing mediation using the difference method, $c - c'$, and the product method $a \times b$. In the next section, the usage of the **khb** R package and its functions will be demonstrated using the same data and examples as the Stata implementation (Kohler et al. 2011).

5.5 Implementation of the KHB Method in R

A user-written program already implementing the KHB method already exists for Stata (Kohler et al. 2011). In R, a basic implementation is provided by the `khb()` function in the **matchingMarkets** package (Klein 2018). The function in this package only works with a single mediator variable and only estimates binary probit models. Moreover, neither of these implementations offers an easy option for calculating nonparametric bootstrapped standard errors and confidence intervals to test for mediation rather than using the Sobel test.

The `khb()` function implemented in the package described here called **khb**, corresponds to the method as outlined by Karlson et al. (2012). It supports models estimated by the `glm()` function from the **stats** package (R Core Team 2020), the `polr()` function from the **MASS** package (Venables and Ripley 2002) and the `multinom()` function from the **nnet** package (Venables and Ripley 2002). It uses the **systemfit** package (Henningsen and Hamann 2007) to estimate the seemingly unrelated regression of the mediators on the explanatory variables. In the case of a categorical mediator with j categories, $j - 1$ seemingly unrelated regressions are estimated. The dependent variable in each case is a binary 0/1 dummy variable for each of the $j - 1$ categories, that is excluding the reference category. If any of the mediating variables are categorical, robust standard errors with finite sample adjustment are calculated for the seemingly unrelated regression using the **sandwich** package (Zeileis 2006).

The `khbBoot()` function also implements the original form of the KHB method, but the standard error and confidence interval of the mediation is obtained using nonparametric bootstrap with the **boot** package (Canty and Ripley 2019; Davison and Hinkley 1997). It applies bootstrap estimation not only to the seemingly unrelated regression of the mediators on the explanatory variables, but also to the reduced model with the residualized mediators as well as the full model to obtain the standard errors of the estimates and 95% confidence intervals. A print method for the results of each of the functions is also provided. The package code, pending submission to the CRAN, is available at `https://gitlab.unige.ch/Dan.Orsholits/khb` and can be installed using the following commands:

```
## Install the khb package
install.packages("devtools")
devtools::install_gitlab(repo = "Dan.Orsholits/khb",
                         host = "gitlab.unige.ch")
```

5.6 Detailed Usage Examples

In this section, the usage of the **khb** package is illustrated using the same examples as those in the article describing the khb user-written command for Stata (Kohler et al. 2011) thus allowing us to compare the two implementations.

Variable	Description
`edu`	Educational attainment (completed compulsory schooling, upper secondary education, or university)
`univ`	Completed university (no/yes)
`fgroup`	Father's social group (lowest, low, middle, high, highest)
`fses`	Father's socioeconomic (standardized continuous)
`abil`	Academic ability (standardized continuous)
`intact`	Intact family (no/yes)
`boy`	Respondent is a boy (no/yes)
`abilCat`	Academic ability (categorical, `abil` split according to quartiles)

Table 5.3 – Description of variables in `dlsy_khb`

The data used in the examples is a subset from the Danish National Longitudinal Survey[1]. It is also used in the article describing the Stata implementation as well as to illustrate the method in Karlson and Holm (2011). Table 5.3 briefly describes the variables in this data set. Additional information is available in Karlson and Holm (2011). The examples here serve to illustrate the mediating effect of academic performance on the relationship between social origin and the completion of higher education. Mediation analysis allows for investigating the degree to which social origin *alone* is responsible for the likelihood of a child completing university, but also the degree to which differences in academic ability due to social origin explain differences in the chances of completing university.

5.6.1 KHB Method

The following examples demonstrate the implementation of the "original" KHB method as described in Karlson et al. (2012). The function `khbBoot()` which estimates standard errors using nonparametric bootstrap will be described in Section 5.6.2.

One Explanatory Variable and One Mediator

In this first example, the aim is to study the mediating effect of academic ability on the relationship between parental socioeconomic status and the completion of

1. It was previously available as part of the online material of the article describing the Stata implementation.

university. Children's sex and the occurrence of family recomposition are included as control variables.

The basic usage of both functions – `khb()` and `khbBoot()` – is the same. First the full model containing the explanatory variable (`fses`), the mediator (`abil`), and the control variables (`boy` and `intact`) is estimated. In this case it is a logistic regression using `glm()`. The tolerance for testing convergence was made stricter than the default settings by changing it to 1×10^{-12} to more closely match the estimates obtained in Stata.

The mediators can be specified as a character vector in the `mediators` argument, or a reduced model excluding the mediators can be supplied via the `reduced_model` argument. The `controls` argument specifies additional control, or concomitant, variables which are not considered to be mediators but should appear in both the full and reduced models.

```
full_model_1 <- glm(univ ~ fses + abil + intact + boy,
                    data = dlsy_khb,
                    family = "binomial",
                    control =
                        glm.control(maxit = 100,
                                    epsilon = 1e-12))
reduced_model_1 <- glm(univ ~ fses + intact + boy,
                       data = dlsy_khb,
                       family = "binomial",
                       control =
                           glm.control(maxit = 100,
                                       epsilon = 1e-12))
test1_khb <- khb(full_model = full_model_1,
                 mediators = "abil",
                 controls = c("intact", "boy"))

## This is another way to call khb()
## The results are the same as the command above
test1_khb_red <- khb(full_model = full_model_1,
                     reduced_model = reduced_model_1,
                     controls = c("intact", "boy"))
```

Displaying the object in the environment uses the `print()` method for the class of the object which is the same as the function name; either `khb` or `khbBoot`. By default, the `print()` method for objects produced using the `khb()` function prints a summary table containing the ratio of confounding (cf. Equation (5.25)), the percentage of confounding – $100 \times (b_{1F^*} - b_{1F})/b_{1F^*}$ where b_{1F^*} and b_{1F} are the regression coefficients in the adjusted reduced and full models respectively – and the rescaling factor (cf. Equation (5.26)). An additional table showing the coefficients for the main variables in the full and reduced models, as well as the difference attributable to confounding by the mediators, is also provided.

```
print(test1_khb)

## Summary of confounding:
##  Variable Confounding Ratio Confounding % Rescale Factor
##      fses          1.430273      30.08326       1.060242
##
##
## Summary of KHB decomposition:
##
## fses:
##         Estimate Std. Error      z  Pr(>|z|)
## Reduced 0.545981   0.077981 7.0015 2.532e-12 ***
## Full    0.381732   0.077806 4.9062 9.286e-07 ***
## Diff    0.164249   0.029325 5.6010 2.131e-08 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

In this example we see that the effect of father's socioeconomic status is 30% larger in the reduced model due to confounding related to children's academic ability. The difference in coefficients between the full and reduced models is also significantly different from zero.

Setting the argument `verbose` to `TRUE` in the print method prints the model summaries for the KHB-corrected reduced model, which corresponds to Equation (5.23) and the original full model supplied to the argument `full_model`.

```
print(test1_khb, verbose = TRUE)

## ##Summary table omitted ##
##
## Model summaries:
##
## Reduced model:
##
## Call:
## glm(formula = univ ~ fses + intact + boy + resid_abil,
##     family = "binomial", data = reduced_data,
##     control = glm.control(maxit = 100, epsilon = 1e-12))
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -1.9950  -0.4315  -0.2778  -0.1658   2.9337
##
##
##
## Coefficients:
##              Estimate Std. Error z value Pr(>|z|)
```

```
## (Intercept) -4.54566    0.74880  -6.071 1.27e-09 ***
## fses         0.54598    0.07798   7.002 2.53e-12 ***
## intactyes    1.12977    0.73870   1.529    0.126
## boyyes       1.06178    0.18481   5.745 9.18e-09 ***
## resid_abil   1.06552    0.10677   9.979  < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 1153.50  on 1895  degrees of freedom
## Residual deviance:  936.63  on 1891  degrees of freedom
## AIC: 946.63
##
## Number of Fisher Scoring iterations: 7
##
##
## Full model:
##
## Call:
## glm(formula = univ ~ fses + abil + intact + boy,
##     family = "binomial", data = dlsy_khb,
##     control = glm.control(maxit = 100, epsilon = 1e-12))
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -1.9950  -0.4315  -0.2778  -0.1658   2.9337
##
## Coefficients:
##             Estimate Std. Error z value Pr(>|z|)
## (Intercept) -4.46300    0.74791  -5.967 2.41e-09 ***
## fses         0.38173    0.07781   4.906 9.29e-07 ***
## abil         1.06552    0.10677   9.979  < 2e-16 ***
## intactyes    1.08391    0.73866   1.467    0.142
## boyyes       0.98214    0.18484   5.314 1.07e-07 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 1153.50  on 1895  degrees of freedom
## Residual deviance:  936.63  on 1891  degrees of freedom
## AIC: 946.63
##
## Number of Fisher Scoring iterations: 7
```

In the output for the reduced model which is estimated using the KHB method, the residualized mediating variables are prefixed with `resid_`. The regression coefficients of the residualized mediating variables are the same as those of their corresponding non-residualized ones in the full model.

Multiple Mediators

In this second example, we treat the control variables in the previous example – `boy` and `intact` – as additional mediators, and no control variables are specified.

```
full_model_2 <- glm(univ ~ fses + abil + intact + boy,
                    data = dlsy_khb,
                    family = "binomial",
                    control =
                        glm.control(maxit = 100,
                                    epsilon = 1e-12))
test2_khb <- khb(full_model = full_model_2,
                 mediators = c("abil", "boy", "intact"))
```

Once again, we obtain the same tables as in the previous example with the default arguments of the `print()` method.

```
print(test2_khb)

## Summary of confounding:
##  Variable Confounding Ratio Confounding % Rescale Factor
##      fses          1.520772      34.24393       1.131706
##
##
## Summary of KHB decomposition:
##
## fses:
##          Estimate Std. Error      z  Pr(>|z|)
## Reduced 0.580528   0.078611 7.3848 1.527e-13 ***
## Full    0.381732   0.077806 4.9062 9.286e-07 ***
## Diff    0.198796   0.034331 5.7905 7.018e-09 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Compared to the previous model, when we consider the sex of the child and whether they live in an intact family as mediators, the amount of confounding increases according to all measures. The difference between the coefficients in the reduced and full models is also larger than in the previous model.

When printing a `khb` object, an additional argument `disentangle` can be passed which produces a table detailing the contribution of each mediator to the overall mediation of a main explanatory variable.

```
print(test2_khb, disentangle = TRUE)

## ## Summary table omitted ##
##
## Components of difference:
##    Mediator   Estimate Std. Error   % Diff. % Reduced
##  Main: fses
##        abil 0.16611771 0.03010585 83.562056 28.614932
##   intactyes 0.02014204 0.01446145 10.132032  3.469606
##      boyyes 0.01253588 0.01152694  6.305912  2.159392
```

This table shows us that the measure of academic ability, `abil`, contributes the most to mediating the relationship between parental socioeconomic status and the completion of university.

Multiple Explanatory Variables

We can also use `khb()` when there is more than one explanatory, or key, variable.

```
full_model_3 <- glm(univ ~ boy + intact + abil + fses,
                    data = dlsy_khb,
                    family = "binomial",
                    control =
                        glm.control(maxit = 100,
                                    epsilon = 1e-12))
test3_khb <- khb(full_model = full_model_3,
                 mediators = "abil",
                 controls = "fses")
```

In this model, the main explanatory variables are boy (sex) and intact family while the mediator is academic ability. Parental socioeconomic status is considered to be a concomitant, or control, variable.

The summary tables produced with the `print()` method show the mediation of each of the main explanatory variables. It shows that academic ability doesn't significantly mediate the effect of either boy or coming from an intact family.

```
print(test3_khb)

## Summary of confounding:
##   Variable Confounding Ratio Confounding % Rescale Factor
##     boyyes          1.081087      7.500530       1.003321
##  intactyes          1.042308      4.059024       1.035420
##
##
## Summary of KHB decomposition:
##
```

```
## boyyes:
##         Estimate Std. Error      z  Pr(>|z|)
## Reduced 1.061780   0.184809 5.7453 9.176e-09 ***
## Full    0.982141   0.184835 5.3136 1.075e-07 ***
## Diff    0.079639   0.133004 0.5988    0.5493
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## intactyes:
##         Estimate Std. Error      z Pr(>|z|)
## Reduced 1.129767   0.738698 1.5294   0.1262
## Full    1.083910   0.738656 1.4674   0.1423
## Diff    0.045858   0.132844 0.3452   0.7299
```

Categorical Mediators and Main Explanatory Variables

Categorical mediators are treated as multiple mediator variables. In this example the mediator `abilCat` is the variable `abil` measuring academic ability grouped into four categories according to the quartiles. The main explanatory variable, `fgroup` measuring the father's social group, is also categorical with five categories. Using dummy coding, this gives us three mediators which are three dummy variables for categories two through four of `abilCat` with the first category being the reference. We also have four main explanatory variables which are four dummy variables for categories two through five of `fgroup` with the first category being the reference.

```
full_model_4 <- glm(univ ~ fgroup + abilCat + intact + boy,
                    data = dlsy_khb,
                    family = "binomial",
                    control =
                        glm.control(maxit = 100,
                                    epsilon = 1e-12))
test4_khb <- khb(full_model = full_model_4,
                 mediators = "abilCat",
                 controls = c("intact", "boy"))
```

When printing the results, we can also ask for the table decomposing the effects of each of the categories of the mediating dummy variable using the `disentangle` argument of the print method. The summary table below shows that, overall, academic ability principally mediates the relationship between university completion and parental socioeconomic status for individuals coming from families of higher socioeconomic status. From the second table obtained with `disentangle = TRUE`, we find that it is principally higher levels of academic ability that mediate the relationship in the case of all socioeconomic groups.

```
print(test4_khb, disentangle = TRUE)

## Summary of confounding:
```

```
##       Variable Confounding Ratio Confounding % Rescale Factor
##      fgroupLow          1.963484      49.07012       1.150064
##   fgroupMiddle          1.672731      40.21753       1.153086
##     fgroupHigh          1.608131      37.81600       1.160852
##  fgroupHighest          1.472821      32.10309       1.147937
##
##
## Summary of KHB decomposition:
##
## fgroupLow:
##         Estimate Std. Error      z Pr(>|z|)
## Reduced  0.66334    0.33078 2.0054  0.04492 *
## Full     0.33784    0.32785 1.0305  0.30280
## Diff     0.32550    0.35400 0.9195  0.35783
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## fgroupMiddle:
##         Estimate Std. Error      z Pr(>|z|)
## Reduced  0.98523    0.30050 3.2786 0.001043 **
## Full     0.58900    0.29586 1.9908 0.046505 *
## Diff     0.39624    0.35561 1.1142 0.265173
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## fgroupHigh:
##         Estimate Std. Error      z  Pr(>|z|)
## Reduced  2.27526    0.33939 6.7040 2.028e-11 ***
## Full     1.41485    0.32400 4.3668 1.261e-05 ***
## Diff     0.86041    0.37288 2.3074   0.02103 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## fgroupHighest:
##         Estimate Std. Error      z  Pr(>|z|)
## Reduced  2.92492    0.41232 7.0938 1.305e-12 ***
## Full     1.98593    0.40187 4.9418 7.742e-07 ***
## Diff     0.93899    0.37109 2.5303   0.01139 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Components of difference:
##             Mediator     Estimate Std. Error     % Diff.   % Reduced
##      Main: fgroupLow
##             abilCat2  0.002343064 0.04863942   0.7198349   0.3532239
##             abilCat3  0.070904333 0.07246519  21.7831949   8.7606627
```

```
##              abilCat4  0.252252756 0.09358103  77.4969702  29.3062508
##   Main: fgroupMiddle
##              abilCat2 -0.027989164 0.04442549  -7.0637662  -2.2676871
##              abilCat3  0.120683746 0.06887132  30.4575641  14.9455637
##              abilCat4  0.303541130 0.08966870  76.6062021  30.8091214
##     Main: fgroupHigh
##              abilCat2 -0.130119503 0.07367912 -15.1229549  -5.7188959
##              abilCat3  0.163343393 0.10248183  18.9843543   6.0945641
##              abilCat4  0.827186690 0.18674217  96.1386005  47.1753279
##  Main: fgroupHighest
##              abilCat2 -0.313073682 0.12523233 -33.3415295 -13.4091393
##              abilCat3  0.145674397 0.14804831  15.5139428   5.8667519
##              abilCat4  1.106389446 0.27352922 117.8275867  37.8262943
```

Ordinal Outcomes

The `khb()` family of functions also supports ordinal regression models estimated using `polr()` from the **MASS** package (Venables and Ripley 2002). Rather than using the binary dependent variable `univ` as in all previous models, we use the polytomous variable `edu` which measures educational achievement.

```
full_model_5 <- polr(edu ~ fses + abil,
                     data = dlsy_khb,
                     control =
                         list(maxit = 20000,
                              reltol = 1e-12),
                     Hess = TRUE)
test5_khb <- khb(full_model = full_model_5,
                 mediators = "abil")
```

The output from the `print()` method shows that same information as in the case of previous models with a binary dependent variable.

```
print(test5_khb)

## Summary of confounding:
##  Variable Confounding Ratio Confounding % Rescale Factor
##      fses          1.360125      26.47734       1.107611
##
##
## Summary of KHB decomposition:
##
## fses:
##         Estimate Std. Error       z  Pr(>|z|)
## Reduced 0.506204   0.048757 10.3821 < 2.2e-16 ***
## Full    0.372175   0.048516  7.6712 1.704e-14 ***
```

```
## Diff    0.134029   0.021315  6.2881 3.214e-10 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

The results are similar to those for the binary model in the first example. We can see that academic ability mediates the association between parental socioeconomic status and the chances of completing a higher level of education.

Multinomial Outcomes

Finally, the `khb()` family of functions also supports multinomial models estimated with `multinom()` from the **nnet** package (Venables and Ripley 2002). The dependent variable is once again `edu` as in the previous example with ordinal regression and the main explanatory variable and mediator are also the same.

```
full_model_6 <- multinom(edu ~ fses + abil,
                         data = dlsy_khb,
                         abstol = 1e-12,
                         reltol = 1e-12,
                         Hess = TRUE)
test6_khb <- khb(full_model = full_model_6,
                 mediators = c("abil"))
```

The main difference in the output is that there are separate confounding values for each outcome category.

```
print(test6_khb)

## Summary of confounding:
##          Variable Confounding Ratio Confounding % Rescale Factor
## Upper secondary:fses        1.349229      25.88362      1.167137
##      University:fses        1.411431      29.14994      1.156446
##
##
## Summary of KHB decomposition:
##
## Upper secondary:fses:
##         Estimate Std. Error      z  Pr(>|z|)
## Reduced 0.422709   0.055406 7.6293 2.360e-14 ***
## Full    0.313297   0.054943 5.7022 1.183e-08 ***
## Diff    0.109412   0.018439 5.9336 2.963e-09 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## University:fses:
##         Estimate Std. Error      z  Pr(>|z|)
## Reduced 0.778842   0.083726 9.3023 < 2.2e-16 ***
```

```
## Full     0.551810   0.082665 6.6753 2.468e-11 ***
## Diff     0.227032   0.037595 6.0388 1.552e-09 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

For each explanatory variable, the outcome is given first with the name for the explanatory variable coming after the colon. For example, the first summary table shows that academic ability accounts for 29% of the total effect of parental socioeconomic status on the completion of university (relative to compulsory schooling). We also have a table for each variable in each outcome showing the difference in coefficients between the reduced and full models. In this case, the reduction of the effect of parental socioeconomic status associated with the inclusion of academic ability is greater in the case of the completion of university than upper secondary education relative to completing compulsory schooling.

5.6.2 KHB Method with Nonparametric Bootstrap

The `khbBoot()` function works in almost the same way as the `khb()` function. The only addition to the function are parameters which control the bootstrap estimation. The parameter `n_bootstraps` sets the amount of replicates. By default it is 1000. The `parallel` and `n_cores` parameters allow the bootstrap to run in parallel and select the number of cores (logical CPUs) allocated. By default, `parallel` is set to `FALSE` and `n_cores` to `NULL`. If `parallel` is `TRUE` and `n_cores` is `NULL`, the number of cores is set using `detectCores()` from **parallel** (R Core Team 2020).

Examples

The first example here is the same as the first example in Section 5.6.1. The difference between the calls to `khb()` and `khbBoot()` is the extra arguments controlling the bootstrap estimation. Here the number of replicates was set to 5000, and parallel estimation was used with eight cores.

```
test1_khbBoot <- khbBoot(full_model = full_model_1,
                         mediators = "abil",
                         controls = c("intact", "boy"),
                         n_bootstraps = 5000L,
                         n_cores = 8,
                         parallel = TRUE)
```

The `print()` method for objects of class `khbBoot` works in the same manner as the one for objects of class `khb` as shown in the previous section. The only difference is an additional parameter `boot_ci_type` which can be `"perc"` for percentile 95% confidence intervals or `"bca"` for bias-corrected and accelerated (BCa) 95% confidence intervals. The default is `"perc"` as the calculation of BCa confidence intervals requires many replications (multiple thousands) and often takes a long time (sometimes longer than the boostrap itself).

Continuing with our example, the first summary table obtained with the print method is the same as for `khb` objects. The summary table for the decomposition is different. Rather than showing the test statistic and associated p-value as with objects of class `khb`, it prints the 95% bootstrap confidence interval, in this case BCa confidence intervals.

```
print(test1_khbBoot, boot_ci_type = "bca")

## Summary of confounding:
##  Variable Confounding Ratio Confounding % Rescale Factor
##      fses          1.430273      30.08326       1.060242
##
##
## Summary of KHB decomposition:
##
## fses:
##           Estimate Std. Error 95% CI lwr 95% CI upr
## Reduced 0.5459815 0.09258586  0.3640347  0.7225075
## Full    0.3817324 0.08986065  0.2042890  0.5575218
## Diff    0.1642491 0.02829795  0.1109573  0.2208962
```

The `verbose` option gives the results of the full and KHB-adjusted reduced model with bootstrap standard errors and bootstrap 95% confidence interval. Here it is used in conjunction with `boot_ci_type = "perc"` to obtain percentile confidence intervals.

```
print(test1_khbBoot, boot_ci_type = "perc", verbose = TRUE)

## Summary of confounding:
##  Variable Confounding Ratio Confounding % Rescale Factor
##      fses          1.430273      30.08326       1.060242
##
##
## Summary of KHB decomposition:
##
## fses:
##           Estimate Std. Error 95% CI lwr 95% CI upr
## Reduced 0.5459815 0.09258586  0.3721298  0.7334064
## Full    0.3817324 0.08986065  0.2079627  0.5629954
## Diff    0.1642491 0.02829795  0.1123886  0.2223022
##
##
##
## Model summaries:
##
## Reduced model:
##                Estimate Std. Error   95% CI lwr 95% CI upr
## (Intercept) -4.5456602 8.05701388 -28.40313047 -3.4880032
```

```
## fses          0.5459815 0.09258586   0.37212976  0.7334064
## intactyes     1.1297672 8.05874347   0.06327248 24.8990516
## boyyes        1.0617798 0.19889515   0.69255590  1.4772463
## resid_abil    1.0655157 0.10209606   0.87861405  1.2836183
##
## Full model:
##                Estimate Std. Error   95% CI lwr 95% CI upr
## (Intercept) -4.4629974 8.04903066 -28.26923618 -3.4210287
## fses          0.3817324 0.08986065   0.20796272  0.5629954
## abil          1.0655157 0.10209606   0.87861405  1.2836183
## intactyes     1.0839097 8.05079518   0.03650978 24.8227183
## boyyes        0.9821406 0.19083001   0.63018595  1.3705607
```

The confidence intervals for the intercept and intact family are very large due to issues with perfect prediction in certain bootstrap samples.

We also illustrate the usage of `khbBoot()` and the `print()` method with model with multiple mediators . First we apply the `khbBoot` function to the full model of the second example in Section 5.6.1 with multiple mediators.

```
test2_khbBoot <- khbBoot(full_model = full_model_2,
                         mediators = c("abil", "boy", "intact"),
                         n_bootstraps = 5000L,
                         n_cores = 8,
                         parallel = TRUE)
```

We can then use the `print` method on the result and request the individual contribution of each mediator. This gives a table with bootstrap standard errors as well as the percentage of difference and reduction due to each mediator.

```
print(test2_khbBoot, disentangle = TRUE)

## Summary of confounding:
##  Variable Confounding Ratio Confounding % Rescale Factor
##      fses          1.520772      34.24393       1.131706
##
##
## Summary of KHB decomposition:
##
## fses:
##          Estimate Std. Error   95% CI lwr 95% CI upr
## Reduced 0.5805281 0.17874223  0.407332755 1.14169767
## Full    0.3817324 0.08986065  0.207962721 0.56299543
## Diff    0.1987956 0.15082945 -0.009769888 0.03946441
##
##
## Components of difference:
```

```
##    Mediator   Estimate Std. Error   % Diff. % Reduced
##  Main: fses
##        abil 0.16611771 0.02806621 83.562056 28.614932
##   intactyes 0.02014204 0.14698744 10.132032  3.469606
##      boyyes 0.01253588 0.01207482  6.305912  2.159392
```

5.7 Comparison with Other Scaling Solutions

Here, the results of KHB method are compared to two other methods, "Y-standardization", a function for models of class `glm` is available in **khb**, and APEs, estimated using the **margins** package (Leeper 2018), for solving the issue of coefficient scaling in non-linear probability models. We also compare these methods to the "naive" solution of simply comparing coefficients between two different models. To compare these methods, we use the reduced and full models from the first example in Section 5.6.1 where the main explanatory is parental socioeconomic status (fses), the mediator is academic ability, and the two control variables are sex and coming from an intact family. Table 5.4 shows the estimated coefficients for the full and reduced models for each method, and the difference of the coefficients. Bootstrap standard errors and percentile confidence intervals are estimated for each of the methods from 5000 replicates.

Method	**Reduced**			**Full**			**Difference**		
	Est.	Std. Err.	95% CI	Est.	Std. Err.	95% CI	Est.	Std. Err.	95% CI
KHB	0.546	0.093	0.372–0.733	0.382	0.090	0.208–0.563	0.164	0.028	0.112–0.222
APE	0.040	0.007	0.027–0.053	0.027	0.006	0.014–0.039	0.013	0.002	0.009–0.018
Y-stand.	0.260	0.065	0.089–0.332	0.170	0.049	0.059–0.243	0.091	0.025	0.024–0.116
Naive	0.515	0.083	0.351–0.682	0.382	0.090	0.208–0.564	0.133	0.029	0.075–0.190

Table 5.4 – Comparison of Different Scaling Solutions for the Effect of Parental SES on University Completion

Comparing the KHB method to the naive estimates, we can see that difference between the coefficients is greater. This shows that estimating mediation without correcting for the issues of different scaling between models will tend to underestimate the degree of mediation (VanderWeele 2016).

If we take the ratio of the estimates, Table 5.5, rather than the difference, we find that the results of the KHB method are relatively close to the APE and "Y-standardization" results. The naive approach leads to a smaller ratio in general (VanderWeele 2016), again suggesting that a direct comparison between different non-linear probability models leads to an underestimation of the mediation. The "Y-standardization" approach gives the highest ratio of all the methods. Using Monte-Carlo simulations, Karlson et al. (2012) have shown that in most situations,

Method	Ratio
KHB	1.430
APE	1.491
Y-stand.	1.534
Naive	1.349

Table 5.5 – Ratios of Estimates of the Effect of Parental SES with Different Scaling Solutions

the KHB, APE, and Y-standardization methods performed similarly, which we can see here, but the KHB method overall performed best and has the lowest mean absolute error in a variety of situations.

5.8 Conclusion

The package **khb** implements the KHB method described by Karlson et al. (2012) for comparing coefficients and testing mediation for regression models with non-continuous outcomes. This method has been shown to perform as well, or better, than other approaches to solve the issue of the scaling of coefficients (Karlson et al. 2012; Breen et al. 2013). The package provides a much improved implementation of the method compared to the existing `khb()` function in the **matchingMarkets** package (Klein 2018) for R. The `khb()` function supports models estimated with `glm()`, `polr()`, and `multinom()`, multiple mediators, multiple explanatory variables, concomitant or control variables. It also supports categorical mediators. This brings its features more or less in line with the Stata user-written `khb` command (Kohler et al. 2011). The results are not, however, identical in all cases due to differences in the estimation of heteroskedastic-consistent standard errors with the **systemfit** and **sandwich** packages (Henningsen and Hamann 2007; Zeileis 2006) for the seemingly unrelated regressions with categorical mediators.

An advantage of this package, **khb**, compared to the Stata implementation, and in line with more recent approaches to mediation analysis(Preacher and Hayes 2004, 2008; Preacher 2015), is that it also implements a nonparametric bootstrap test version to test for mediation as an alternative to the test proposed in (Karlson et al. 2012). Thus, this package also extends the KHB approach to assessing mediation in non-linear probability models.

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Chapter 6 The Great Recession and Trajectories of Vulnerability to Unemployment in the UK and Switzerland[1]

6.1 Introduction

The Great Recession had a profound impact on the labour market. Unemployment increased substantially and rapidly in almost all developed countries in the aftermath (Keeley and Love 2010). While the unemployment rate began to decrease shortly after the crisis, this did not necessarily translate into a return to pre-recession levels (Curci et al. 2012). In fact, it took ten years for employment levels to recover to pre-2008 levels (OECD 2018, 11).

To date, most of the focus on the relationship between the Great Recession and the labour market has been at the aggregate level. Analyses using aggregate data have shown that certain groups of workers, such as those outside the service sector or younger individuals, were more likely to enter unemployment. The same applies to workers in non-standard forms of employment such as part-time and/or fixed-term work (Keeley and Love 2010; Cho and Newhouse 2013; Pissarides 2013).

However, the consequences at the individual level in relation to vulnerability to unemployment and its evolution over time are comparatively less investigated. In this chapter, vulnerability to unemployment is conceptualized as an individual's *latent* risk of experiencing unemployment at a given point in time. The aim is to describe individual trajectories of vulnerability to unemployment in the medium term during the Great Recession in relation to individual characteristics using longitudinal panel data. Individual-level data allows us to take into account within- and/or between-individual differences in the evolution of vulnerability to unemployment. This allows us to go beyond investigating aggregate labour market outcomes and focus on how individuals were able to cope with a generalized increase in the risk of unemployment.

Another goal is to compare the UK and Switzerland by highlighting differences in the evolution of vulnerability to unemployment. Contrasting the UK and Switzerland allows us to observe changes in vulnerability to unemployment in two countries which experienced the crisis very differently. Switzerland was relatively unaffected by the crisis (van Ours 2015) while the UK was among the first countries to experience the financial crisis and subsequent rise in unemployment even if it wasn't the most strongly affected country in terms of labour market outcomes in Europe.

In this application, we take a holistic approach to studying vulnerability to unemployment over time by using growth curve models. Instead of decomposing trajectories

1. A version of this chapter has been published as a LIVES Working Paper: Dan Orsholits et al. 2019. "The great recession and trajectories of vulnerability to unemployment in the UK and Switzerland." *LIVES Working paper* 79:1–31. `https://doi.org/10.12682/lives.2296-1658.2019.79`

into discrete transitions and risk losing the sight of the larger picture (Piccarreta and Studer 2018), growth curve models allow us to examine trends in the change of vulnerability to unemployment over time during the Great Recession, but also differences in trajectories between individuals, in a broader perspective. Moreover, growth curve models are better suited to studying panel data where individuals' current situations or attributes are followed over time (Grimm, Ram, and Estabrook 2017, 29) than other longitudinal methods such as event history analysis which are more suited to investigating transitions or changes. In addition, we are able to demonstrate the usefulness of these models in two different contexts: one where we expect little to no change in vulnerability to unemployment over time and another where we *do* expect change over time.

The chapter is organized as follows: first the Great Recession and its consequences for the labour market, particularly in the case of the UK and Switzerland, are briefly reviewed. Second, the vulnerability framework presented in Section 3.3 is operationalized using latent growth curve models. Third, individual trajectories of vulnerability to unemployment are estimated using latent growth curve models and compared within, and between, the UK and Switzerland.

6.2 The Great Recession and the Labour Market

As we saw in Section 2.1, the Great Recession finds its roots in the collapse of the subprime mortgage market in the United States and the ensuing financial crisis. The high level of interconnectedness of financial markets in the Western world coupled with the participation of non-US banks in the mortgage securities market meant that the crisis spread quickly to most of Western Europe (Fligstein and Habinek 2014; Pernell-Gallagher 2015). This led to a sharp increase in the unemployment rate in many countries and the steepest economic decline since the Great Depression.

In the US, the unemployment rate increased constantly between 2008 and 2010 and only began to decline in 2011. Moreover, the employment rate among prime-age workers – 25–54 year-olds – was very slow to recover (Redbird and Grusky 2016, 191). Europe didn't fare much better but there were substantial differences between countries in the rise of the unemployment with some countries even seeing *decreases* (Tåhlin 2013; Tridico 2013). These differences are partially attributed to institutional factors such as the existence of short-time work programmes and, as Tridico (2013) argues, labour market flexibility. Comparing European countries in relation to the OECD employment protection legislation (EPL) indicator, he finds that countries with stronger social institutions, and therefore less flexible labour markets, were less affected. Broadly this group of countries corresponds to coordinated market economies (CMEs) in the varieties of capitalism typology.

The UK being a liberal country (Esping-Andersen 1990) – and thus having a flexible labour market – was consequently more affected by the crisis especially concerning employment. The case of Switzerland is more complicated. While it is generally considered to be a CME, or being part of the conservative regime, (Esping-Andersen 1990; Hall and Soskice 2001; Hall and Gingerich 2009), Switzerland's labour market has more in common with liberal countries as employment regulation is more lax than comparable countries especially when it comes to the ability of employers to dismiss workers (Emmenegger 2010). According to the OECD's employment protection legislation (EPL) index, Switzerland is among the countries with the *weakest* protections for employees with its score being on par with that of liberal countries such as the UK, Canada, or Australia (OECD 2020, 186). The same is true for collective and mass dismissals where only the US is less strict than Switzerland while the UK finds itself closer to the middle of the pack (189–190).

As for access to unemployment benefits, both the UK and Switzerland implement active labour market policies which require individuals to actively search for jobs in order to be eligible to receive unemployment benefits (Langenbucher 2015, 18). However, in terms of the income replacement rate provided by unemployment benefits, Switzerland is far generous than the UK with a replacement rate of around 74% for a single individual making the average national wage in 2009 versus 55% in the UK (OECD 2019).

Beyond employment regulation, especially in relation to dismissals, there are nevertheless other differences that should be taken into account. Being a CME, Switzerland, like neighbours Austria and Germany, has a dual-education system which, as we saw in Section 2.2.1, is more likely to reduce the potential increase of youth unemployment following the crisis. Switzerland also has a provision for short-time work schemes, as in the case of Germany, which were shown, by Tridico (2013), to reduce the negative labour market consequences of the crisis.

In addition to differences between countries, not all workers were as likely to be negatively affected by the crisis. As we saw in Section 2.2 women were less affected be the increase in unemployment. This can in part be attributed to a larger presence of men working in the sectors that were harder hit by the crisis such as construction or manufacturing (Keeley and Love 2010; Pissarides 2013). In the UK more specifically, Tåhlin (2013) finds that unemployment among women didn't increase as sharply after the crisis (see also Figure 6.1) as for men which is in line with the general trend in the OECD. In Switzerland, the unemployment rate increased for both men and women (Figure 6.2), however the increase was more pronounced for men with gap between unemployment rates for the two sexes narrowing over time.

The crisis also disproportionately affected younger workers. Looking at more recent data for the UK (Figure 6.1), we see a clear difference in the increase in the unemployment rate between age groups with younger age groups seeing more substantial increases. However in the UK, the increase in the unemployment rate for younger workers (20–29) relative to prime-age workers was lower than in most other European countries (Tåhlin 2013) and generally less pronounced than in previous crises (Gregg and Wadsworth 2010). In Switzerland (Figure 6.2), the unemployment rate is consistently highest for the youngest (15–24), but it doesn't seem to show a clear pattern towards a long-term increase. The unemployment rate for older workers did increase but it began to decline shortly after the crisis (OFS 2018). Thus, while we would expect younger individuals to be more likely to experience to unemployment, the difference relative to older individuals over time should be less substantial in Switzerland than in the UK.

In relation to the level of education, the unemployment rate for individuals with less than a secondary in the UK level was much higher than for other educational categories (Gregg and Wadsworth 2010). We can see that the increase was more pronounced for this group relative to the other (Figure 6.1), however the unemployment rate nevertheless declined over time. In Switzerland, educational differences are less pronounced. The general trend is of relative stability in the unemployment rate (Figure 6.2) for all educational groups though it seems slightly more pronounced for the lowest educated. In summary, the 2008 Financial Crisis and the ensuing recession led to a general increase in unemployment but there was substantial variation between countries. In choosing to compare the UK and Switzerland, we compare a country that was among the first to be hit by the crisis to another that was relatively unaffected.

However, the analyses presented here do not go beyond describing differences in the aggregate unemployment rate between groups and thus do not investigate differences in *vulnerability* to – or the latent risk of – unemployment during the Great Recession. The aim of this chapter is to go beyond aggregate-level labour market outcomes and focus on individual trajectories of vulnerability to unemployment in the medium term. That is, we investigate whether individuals' degree of vulnerability to unemployment changes over time in relation their characteristics. For example, in the case of younger workers we are interested not only in their overall vulnerability to unemployment, but also whether their vulnerability to unemployment declined over time as the economy recovered relative to other age groups.

6.3 Vulnerability & The Great Recession

While most of the work presented in the previous section focused on labour market outcomes at the macro level, here we focus on whether the crisis increased individuals' latent risk of becoming unemployed in the short and medium term i.e. whether certain individuals became more *vulnerable* in a period covering 8 years after the crisis occurred. In this section we briefly reintroduce the dynamic vulnerability framework presented in Section 3.3.

Drawing on work in psychology and sociology on stress process models (Pearlin et al. 1981; Pearlin 1989, see also Kessler 1979; Turner and Noh 1983; Kessler and McLeod 1984; Aneshensel 1992), we follow the framework proposed by Spini et al. (2013, 19) and Spini et al. (2017, 8). In this framework vulnerability is considered as a process resulting from the potential of experiencing negative consequences when exposed to sources of stress in a specific context. The vulnerability *process* is considered to have three elements or stages: *risk*, *coping*, and *recovery*.

In our particular case, the stressor is the Great Recession and the negative consequence is being unemployed. One particularity of the Great Recession is that it is a stressor that affected everyone. As such, contrary to other stressors (divorce, unemployment, etc.), differential exposure – that is individual differences in the risk of experiencing the stressor – is not an issue. Thus, the first stage of vulnerability, risk, is not our focus. Instead here we focus on the second and third stages: coping and recovery.

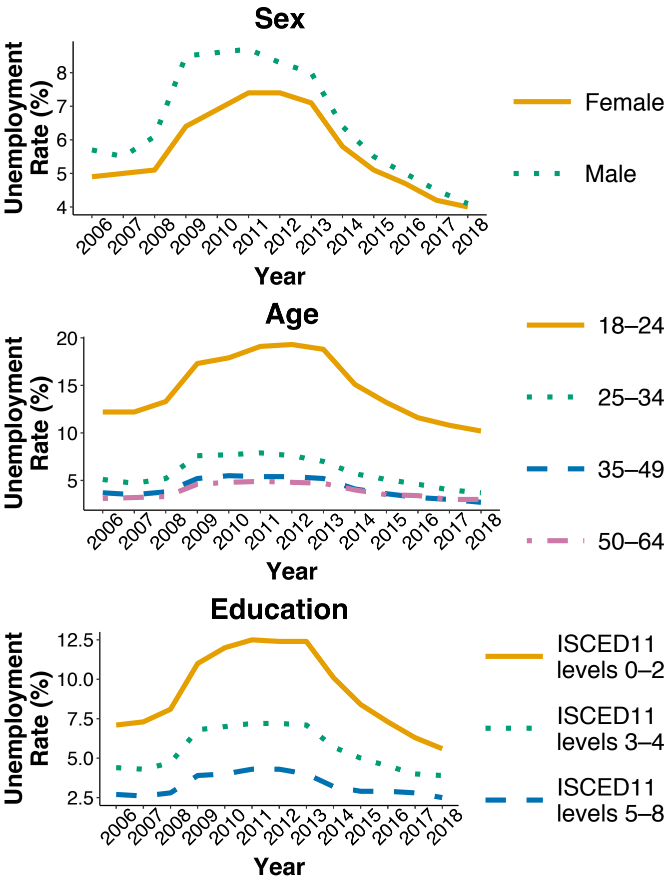

Figure 6.1 – Unemployment Rates for UK; Sources: Eurostat and UK LFS

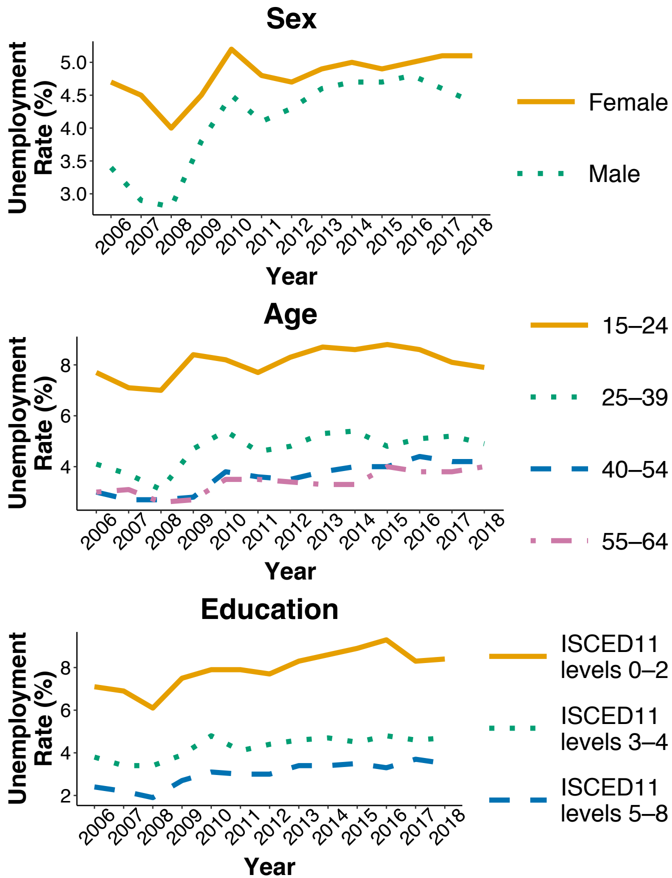

Figure 6.2 – Unemployment Rates for Switzerland; Source: Swiss Federal Statistics Office

With the use of individual-level longitudinal data, we can describe individuals' vulnerability to unemployment in the short and medium term. These trajectories can show us how individuals coped with and recovered from effects of the Great Recession in relation to their individual characteristics and resources. If certain individuals see a less marked increase relative to others in terms of their chances of being unemployed in the immediate aftermath of the crisis, we can consider that they were better able to cope with the negative consequences of the crisis. When looking at the patterns of change in vulnerability to unemployment over time, we can investigate differences in the ability to recover from the negative consequences of the Great Recession.

Based on this model of vulnerability, we can formulate three main hypotheses relative to trajectories of vulnerability to unemployment in the Great Recession, and individual resources and characteristics. First, men were disproportionately affected by the crisis relative to women principally due to male-dominated sectors being more substantially affected. We can hypothesize that:

Hypothesis 1a Initially, males were more vulnerable as they were more likely to experience unemployment relative to females.

Hypothesis 1b Men became less vulnerable over time as the economy began to recover.

These hypotheses are based on aggregate data showing that the unemployment rate for men increased more substantially than the unemployment rate for women following the crisis (Keeley and Love 2010; Pissarides 2013).

Generally younger individuals are more vulnerable relative to older individuals as they are more often unemployed (Russell and O'Connell 2001) and we would expect them to be more affected by changes in the economic situation relative to older workers (Keeley and Love 2010, 4).

Hypothesis 2a Younger individuals were initially more likely to enter unemployment following the crisis.

However, we may also expect those who were youngest to become less vulnerable over time as the economy recovered and labour demand rose increasing their chances of finding a job.

Hypothesis 2b Over time, younger individuals should become less vulnerable relative to older individuals.

In relation to the level of education, we would expect that individuals with lower levels of education would have been more likely to enter unemployment as the crisis hit as the Great Recession mainly affected jobs outside the service sector that typically require lower levels of education.

Hypothesis 3a Initially, individuals with lower levels of education were more likely to enter unemployment after the crisis.

However, it is less clear how the odds of unemployment would change over time for the lowest educated. Following recovery, we would expect these individuals to find jobs and possibly see their chances of unemployment decrease over time relative to more highly educated individuals. Another possibility is that such individuals were replaced by more highly educated individuals who took jobs below their qualifications in order to avoid unemployment and to cope with the recession. Thus individuals with fewer qualifications would see their unemployment prolonged leading to an increase in the odds of unemployment over time.

Hypothesis 3b Over time, individuals with lower levels of education should see their vulnerability to unemployment change.

However, the direction of the change over time is uncertain.

6.4 Methods & Data

This chapter applies a dynamic definition of vulnerability using longitudinal data from the Swiss Household Panel (SHP), the British Household Panel (BHPS), and Understanding Society: The UK Household Longitudinal Study (UKHLS) and latent growth curve models. The negative outcome that is investigated is unemployment and the stressor is the 2008 Financial Crisis. The dependent variable is a binary indicator of whether individuals are unemployed or employed.

6.4.1 (Latent) Growth Curve Models

If we consider vulnerability as being a dynamic process, it is necessary to employ longitudinal data to understand it, but the insights gained from the available data depend on the methods used. Latent growth curve models allow estimating trajectories of change in a variable over time. They focus on describing differences *between* individuals and how differences in individual characteristics can explain differences in the change of the dependent variable over time. This considers that vulnerability is not a single outcome – just entering unemployment – but is a process and allow us to take a holistic approach to studying vulnerability. As such, if we consider the possibility of "measurable" vulnerability, growth models can tell us the effect of a variable on the trajectory of the outcome across time and the differences between individuals' trajectories (Halaby 2003, 515; McArdle and Nesselroade 2014, 161).

Our main interest is to describe trajectories of vulnerability to unemployment – or the latent risk of experiencing unemployment – and differences between individuals over time. As we saw in Chapter 4, not all longitudinal data methods are suited to analysing these types of research questions. Growth curve models are a good choice especially as they are designed to model between-individual heterogeneity over time unlike approaches using fixed effects models which are generally not designed to do so.

Growth models can be implemented using structural equation (SEM) or multilevel models and the results are often identical or very similar (Chih-Ping Chou et al. 1998; Curran 2003), but the two approaches have their advantages and disadvantages as not all types of growth models can be estimated by both frameworks (Ghisletta and Lindenberger 2004, 13; Ram and Grimm 2009; Grimm, Ram, and Estabrook 2017, 10–12). We chose to model vulnerability to unemployment using latent growth curve models in the SEM framework. This choice stems from certain SEM software packages – Mplus – being able to estimate growth curve models with a categorical outcome more reliably and in a shorter amount of time (Grimm, Ram, and Estabrook 2017, 341).

Model Specification

Mathematically, a latent growth curve model can be expressed as follows in the structural equation framework[2]:

$$\boldsymbol{y}_i = \boldsymbol{\Lambda}\boldsymbol{\eta}_i + \boldsymbol{\epsilon}_i = \boldsymbol{\Lambda}(\boldsymbol{\mu} + \boldsymbol{\zeta}_i) + \boldsymbol{\epsilon}_i \tag{6.1}$$

where $\boldsymbol{y}_i$ corresponds to a vector of length T which contains the observations of y for an individual i at successive time points.

In the case of a binary dependent variable y^* – in our case being unemployed – the left-hand term in Eq. (1) is the vector of logits at the successive time points of the category of interest $y^* = 1$:

$$y_{it} = \ln\left(\frac{P(y^*_{it} = 1)}{1 - P(y^*_{it} = 1)}\right)$$

This is the basic equation for a growth curve model. The $\boldsymbol{\Lambda}$ matrix and the $\boldsymbol{\eta}_i$ vector change according to the specified model. The $\boldsymbol{\Lambda}$ matrix contains the loadings – the time scores – for the latent factors that describe the trajectory of change over time for the dependent variable. The $\boldsymbol{\eta}_i$ vector can be decomposed into two other vectors: the $\boldsymbol{\mu}$ vector containing the means of the estimated latent factors describing the trajectory and the ζ_i vector containing the individual-specific deviations from the factor means. In our specific case, the $\boldsymbol{\mu}$ vector describes the average trajectory of vulnerability to unemployment while the $\boldsymbol{\zeta}_i$ vector takes into account the individual heterogeneity of trajectories, that is individual deviations from the average trajectory of vulnerability to unemployment. The length of the $\boldsymbol{\mu}$, ζ_i, and $\boldsymbol{\eta}_i$ vectors is the same as the number of estimated latent factors.

In the case of a linear model, there are two latent factors describing trajectories: a slope and an intercept. The $\boldsymbol{\Lambda}$ matrix containing the factor loadings (time scores) and the $\boldsymbol{\mu}$ and $\boldsymbol{\zeta}_i$ vectors are:

$$\boldsymbol{\Lambda} = \begin{pmatrix} 1 & 0 \\ 1 & 1 \\ 1 & 2 \\ \vdots & \vdots \\ 1 & T-1 \end{pmatrix} \text{ and } \boldsymbol{\eta}_i = \begin{pmatrix} \mu_\alpha \\ \mu_\beta \end{pmatrix} + \begin{pmatrix} \zeta_{\alpha_i} \\ \zeta_{\beta_i} \end{pmatrix}$$

2. Here I follow the notation in Kenneth A. Bollen and Patrick J. Curran. 2006. *Latent Curve Models: A Structural Equation Perspective.* John Wiley & Sons

with μ_α corresponding to the mean of the intercept factor and μ_β to the mean of the slope factor, and ζ_{α_i} and ζ_{β_i} being the individual deviations from the intercept and slope respectively.

More concretely, the first latent factor – the intercept factor – is the initial latent level, that is the level of vulnerability at the first time point (McArdle and Nesselroade 2014, 94). The other time-varying factors describe the change in vulnerability to unemployment between measurements.

As we are interested in comparing trajectories between individuals, we include time-invariant covariates (TICs), in other words a *conditional* latent growth curve model, with the TICs being regressed on the latent factors describing the trajectories of vulnerability to unemployment. Thus, it is possible to distinguish between more and less vulnerable trajectories depending on certain time-invariant characteristics. A conditional latent growth curve model can be expressed as follows:

$$\boldsymbol{y}_i = \boldsymbol{\Lambda}\boldsymbol{\eta}_i + \boldsymbol{\epsilon}_i = \boldsymbol{\Lambda}(\boldsymbol{\mu} + \boldsymbol{\zeta}_i + \boldsymbol{\Gamma}_x \boldsymbol{x}_i) + \boldsymbol{\epsilon}_i \tag{6.2}$$

Compared to equation 6.1 there are two new terms: Γ_x, and x_i. Γ_x is an $m \times n$ matrix containing the regression coefficients of the time-constant *manifest* independent variables x_i on the latent factors where m is the number of latent factors, and n is the number of manifest TICs. x_i is a vector containing the observed values of the n manifest TICs for an individual i. When adding in TICs, individuals' trajectories become a function of the mean trajectory, their individual deviation from the mean trajectory, and their time-constant individual characteristics. In other words, we estimate the effect individual characteristics can have on trajectories of vulnerability to unemployment.

6.4.2 Data

For Switzerland, 9 waves of data covering a period ranging from 2007 to 2015 from the SHP were used. While more recent data is available for the SHP, we restricted it to 2015 for parity with UK panel data. For the UK, to cover the same period, data had to be taken from two surveys: the BHPS and the UKHLS. Data collection for the BHPS stopped in 2008. However, former participants were invited to join the successor survey, the UKHLS, starting from 2010. Unfortunately, that means there is no data available for former BHPS participants in 2009. Thus, the final two waves of the BHPS covering 2007 and 2008 were used in conjunction with six waves from the UKHLS covering 2010 to 2015.

Employment status is a binary variable with two categories: employed (0) and unemployed (1). Respondents under the age of 18 and over the age of 53 in 2007 were excluded so as to avoid including individuals who may have reached the mandatory retirement age by 2015 (65 for men in both the UK and Switzerland, and 63 and 64 for women in the UK and Switzerland respectively). Participants were included regardless of their employment status in 2007.

The covariates are measured in 2007, the year before the financial crisis, for both the UK and Switzerland. The following covariates are added sequentially to a basic model containing no covariates: 1) employment status (employed, unemployed, out of labour force); 2) sex; 3) age (4 categories: 18–24, 25–34, 35–44, 45+); 4) education (3 categories: less than upper secondary, upper secondary, tertiary). The reference individual, once all of the covariates are included, is a male who in 2007 was employed, aged between 35 and 44, and who had completed an upper secondary level of education.

6.5 Results

Five linear latent growth curve models were estimated for the UK and Switzerland in Mplus 7.4 (Muthén and Muthén, 1998–2015) using a robust full-information maximum likelihood estimatior allowing missing data on the dependent variable. The data preparation was done with R (R Core Team 2018) and the MplusAutomation package (Hallquist and Wiley 2018). The dependent variable takes the value 1 if an individual is unemployed at a certain time t and 0 otherwise.

The first model – Model 0 – is an unconditional linear growth curve model (i.e. without covariates). Model 1 controls for individuals' employment situations in 2007. Model 2 includes individuals' sex in order to test for differences between men and women (Hypotheses 1a and 1b). Model 3 adds individuals' age prior to the crisis in 2007 in order to test for differences in the risk of unemployment across different age groups (Hypotheses 2a and 2b). Finally, Model 4 takes into account individuals' highest level of education in order to test Hypotheses 3a and 3b concerning differences between educational groups. In the final model, the reference individual is a male, who was employed in 2007, aged between 35 and 44, with an upper secondary level of education.

The results of the models are presented in two parts. The first shows the estimates for the latent factors, $\boldsymbol{\mu}$ in Equation (6.2), that describe the trajectories of vulnerability to unemployment. The intercept can be interpreted as an overall level of vulnerability in 2008. The slope factor can be interpreted as the overall *change* in vulnerability over a 1-unit increase in time, that is the increase or decrease in the overall level of vulnerability. The variances of the latent factors are also reported.

The second part of the results show the regressions of the latent factors on the covariates, $\boldsymbol{\Gamma}_x$ in Equation (6.2). The coefficients in the column for the intercept latent factor can be interpreted as the overall time-constant difference between different groups of individuals. They are analogous to fixed effects coefficients in a multilevel regression.

The coefficients in the column for the slope latent factor can be interpreted as the difference between groups in the change in vulnerability over time, that is the difference in trajectories of vulnerability. This is analogous to an interaction between time and a covariate in the case of growth curve models estimated within the multilevel modelling framework (Grimm, Ram, and Estabrook 2017, 95).

6.5.1 Switzerland

Looking at the intercept factor means in Table 6.1, the estimates suggest a very low overall vulnerability to unemployment. If we exponentiate the coefficient of the intercept to get odds ratios, we see that in Model 0 the overall odds ratio of being unemployed for the reference group (employed males, aged between 34 and 44 with complete upper secondary education) is smaller than 0.002 in all models. The variance of the intercept factor is however significantly different from zero in all five models suggesting that while the overall risk is low, there is significant inter-individual heterogeneity in vulnerability to unemployment.

Things aren't so clear for the slope factor. Initially it is non-significant suggesting no real overall change in vulnerability over time. However once sociodemographic characteristics are taken into account, the mean of the slope factor becomes larger and even significantly different from 0 in Models 3 and 4. This suggests that over time, individuals in our reference group, males aged 35–44, became *more* vulnerable as their chances of being unemployed increased. Exponentiating the coefficients for the slope factor in Models 3 and 4, we get odds ratios of approximately 1.31 and 1.36 which indicates that there is an increase of 31% and 36% in the odds of being unemployed over one year respectively. The variance becomes non-significant when including the sociodemographic variables suggesting that the variance in the slope factor, i.e. inter-individual heterogeneity in change over time, is at least partially explained by differences related to employment status in 2007 and individuals' sex.

Looking at employment status in 2007, we find that individuals who were not in employment are overall more vulnerable. What's more interesting is that over time, individuals who were initially out of employment or unemployed become less vulnerable relative to those who were in employment as their chances of being unemployed decreased. This suggests that the crisis didn't reduce chances for those out of employment to later re-enter employment. The results of the regression of the latent intercept factor on the covariates show that individuals who were not employed in 2007 were significantly more likely to be or remain unemployed overall.

Returning to Hypothesis 1 relating to differences between sexes, we find the women were more likely to be unemployed relative to men overall. Exponentiating the coefficients, the odds ratios show that individuals of the female sex were approximately two times more likely to be unemployed over all than men. This is contrary to what was expected and consequently Hypothesis 1a is rejected. Looking at differences over time – Hypothesis 1b – we find that women relative to men become less vulnerable. The odds of women being unemployed, relative to men, decrease approximately by between 12 and 14% per year if we look at Models 2 through 4. Thus, in the time since the crisis, the likelihood of being unemployed decreased for women relative to men. This leads us to reject the hypothesis which posited that men would become less vulnerable over time.

Looking at the different age groups, we find that overall individuals in the youngest group were more vulnerable as their odds of being unemployed were highest. Exponentiating the coefficients, we get odds ratios of around 3.2 and 2.5, for Models 3 and 4 respectively, showing that younger are individuals are at least two-and-a-half times more likely to be unemployed overall. These results are in line with Hypothesis 2a. For the other age groups, there are no significant differences relative to our reference 35–44 age group. Concerning changes in vulnerability over time – Hypothesis 2b –, there seems to be no difference between age groups relative to the reference group. Thus, Hypothesis 2b stating that younger individuals

	(0)		(1)		(2)		(3)		(4)	
	Intercept Factor	Slope Factor	Intercept Factor	Slope Factor	Intercept Factor	Slope Factor	Intercept Factor	Slope Factor	Intercept Factor	Slope Factor
Factor Mean	−6.706***	0.075	−6.522***	0.016	−7.590***	0.244	−7.825***	0.273*	−7.742***	0.308*
	(0.421)	(0.092)	(0.375)	(0.086)	(0.589)	(0.128)	(0.606)	(0.129)	(0.641)	(0.141)
Factor Variance	7.875***	0.069**	5.187***	0.044*	5.222***	0.040	5.049***	0.039	4.970***	0.037
	(1.546)	(0.026)	(1.061)	(0.022)	(1.065)	(0.022)	(1.012)	(0.022)	(1.010)	(0.022)
Covariance	−0.398		−0.117		−0.107		−0.094		−0.092	
	(0.211)		(0.151)		(0.150)		(0.144)		(0.145)	
Regressions										
Employment status 2007 (Ref: Employed)										
Unemployed			4.567***	−0.294*	4.582***	−0.303*	4.310***	−0.295*	4.305***	−0.296*
			(0.549)	(0.124)	(0.553)	(0.123)	(0.548)	(0.121)	(0.544)	(0.121)
Out of labour force			2.915***	−0.301**	2.835***	−0.286**	2.489***	−0.274**	2.419***	−0.276**
			(0.382)	(0.091)	(0.382)	(0.092)	(0.392)	(0.093)	(0.391)	(0.093)
Sex (Ref: Male)										
Female					0.664**	−0.131*	0.792**	−0.143*	0.778**	−0.152**
					(0.256)	(0.056)	(0.257)	(0.056)	(0.259)	(0.058)
Age (Ref: 35–44)										
18–24							1.189**	−0.097	0.920*	−0.109
							(0.345)	(0.078)	(0.388)	(0.093)
25–34							−0.307	−0.013	−0.237	−0.021
							(0.369)	(0.076)	(0.368)	(0.077)
45+							−0.189	−0.038	−0.196	−0.040
							(0.309)	(0.068)	(0.311)	(0.068)
Education (Ref: Upper secondary)										
Less than upper sec.									0.577	−0.014
									(0.389)	(0.097)
Tertiary									−0.188	−0.035
									(0.278)	(0.060)

Table 6.1 – Results for Switzerland
N = 3,685; N obs. = 22,492; Std. errors in brackets
*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$
Data Source: Swiss Household Panel

would become less vulnerable over time, is rejected.

Looking at educational groups, Hypothesis 3a is rejected as there are no significant differences between individuals with an upper secondary level of education, and those having completed tertiary or less-than-upper-secondary education. Thus contrary to the hypothesis, individuals with lower levels of education are not overall more likely to experience unemployment. Nevertheless, there would seem to be a trend of lower educated individuals being more likely to enter unemployment.

As for changes in vulnerability over time in relation to the level of education – Hypothesis 3b – , there are no significant differences between individuals with a tertiary level or those with less than an upper secondary level of education relative to the reference category. Consequently the hypothesis is rejected as individuals with lower levels of education do not become more vulnerable over time in Switzerland.

6.5.2 United Kingdom

The estimates for the latent factor means (Table 6.2) suggest a low overall vulnerability to unemployment which was also the case for the Swiss results. Exponentiating the coefficient for the intercept factor we obtain an odds ration smaller than 0.002 for all models for the reference group. However in contrast to Switzerland, the slope factor is negative and significantly different from zero indicating an overall decline in vulnerability to unemployment over time. The odd ratio varies from around 0.81 (Model 0) to 0.73 (Model 4) indicating a decline of approximately 20% to 30% per year in the chances of being unemployed. The estimated variance for the latent intercept factor is rather large but is subsequently reduced with the inclusion of the covariates suggesting that some of the inter-individual heterogeneity can be explained by sociodemographic characteristics. The estimated variance for the slope factor is significantly different from zero in all models suggesting that even once the covariates are taken into account, inter-individual differences in the change in vulnerability over time remain.

Looking at the regressions of the latent factors on the covariates, we find that employment status in 2007 only really matters for the overall level of vulnerability. Individuals who were not in employment in 2007 were overall more likely to be unemployed. However, they weren't significantly more likely to be unemployed over time relative to individuals who were employed in 2007.

Looking at sex, in all models women are overall less likely to be unemployed than men after the crisis which is in line with Hypothesis 1a. Exponentiating the coefficient for female indicates that women are between 2.4 (Model 2) and 2.1 (Model 4) times less likely than men to be unemployed. However, there is no significant difference between men and women in change over time contrary to Hypothesis 1b which stated that over time men would become less vulnerable as they would start to return to employment.

As for the different age groups, individuals in the two youngest age groups were overall more vulnerable which is in line with Hypothesis 2a as they were more likely to be unemployed. Taking odds ratios, individuals in the youngest age group were 2.3 (Model 3) and 2.4 (Model 4) times more likely to be unemployed while those in the 25–34 group were 1.75 (Model 3) to 2 (Model 4) times more likely to be unemployed. For those that were youngest, 18–24 in 2007, we also find that they

	(0)		(1)		(2)		(3)		(4)	
	Intercept Factor	Slope Factor	Intercept Factor	Slope Factor	Intercept Factor	Slope Factor	Intercept Factor	Slope Factor	Intercept Factor	Slope Factor
Factor Mean	−7.365***	−0.210*	−7.276***	−0.276**	−5.927***	−0.322**	−6.181***	−0.310**	−6.090***	−0.320**
	(0.451)	(0.099)	(0.400)	(0.091)	(0.468)	(0.107)	(0.503)	(0.116)	(0.511)	(0.118)
Factor Variance	24.027***	0.248***	12.837***	0.244***	12.651***	0.238***	12.235***	0.244***	11.228***	0.229***
	(4.024)	(0.048)	(1.801)	(0.039)	(1.814)	(0.039)	(1.763)	(0.040)	(1.664)	(0.038)
Covariance	0.260		0.204		0.210		0.255		0.169	
	(0.386)		(0.211)		(0.211)		(0.202)		(0.190)	
Regressions										
Employment status 2007 (Ref: Employed)										
Unemployed			7.894***	−0.004	7.824***	0.001	7.516***	0.084	6.852***	0.015
			(0.549)	(0.123)	(0.550)	(0.124)	(0.549)	(0.126)	(0.514)	(0.117)
Out of labour force			5.086***	−0.025	5.970***	−0.025	5.646***	0.051	5.217***	−0.001
			(0.439)	(0.094)	(0.446)	(0.096)	(0.447)	(0.098)	(0.421)	(0.091)
Sex (Ref: Male)										
Female					−0.897**	0.031	−0.859***	0.025	−0.730***	0.033
					(0.200)	(0.047)	(0.198)	(0.047)	(0.195)	(0.046)
Age (Ref: 35–44)										
18–24							0.885**	−0.185**	0.831**	−0.161*
							(0.300)	(0.071)	(0.293)	(0.070)
25–34							0.563*	−0.115	0.693**	−0.107
							(0.258)	(0.061)	(0.255)	(0.060)
45+							−0.076	0.156*	−0.121	0.149*
							(0.274)	(0.064)	(0.272)	(0.063)
Education (Ref: Upper secondary)										
Less than upper sec.									1.694***	0.186**
									(0.267)	(0.065)
Tertiary									−1.006***	−0.008
									(0.240)	(0.055)

Table 6.2 – Results for the United Kingdom

N = 7,058; N obs. = 32,858; Std. errors in brackets

*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$

Data Sources: British Household Panel & Understanding Society became less vulnerable over time. Their odds of being in unemployment relative to the reference age group, 0.83 and 0.85 and for Models 3 and 4 respectively, decrease by around 15% per year. The trend for the 25–34 age group is similar, however the estimates are not significantly different from zero. These results also support Hypothesis 2b which stated that younger individuals would become less vulnerable over time as the economy began to recover.

Interestingly, we find that individuals who were in the oldest age category (45+) in 2007, became *more* vulnerable over time relative to the reference age group. Odds ratios of 1.17 and 1.16 for Models 3 and 4 indicate a 16 and 17% increase per year in the odds of being unemployed. This may suggest that the consequences of the crisis for older individuals were delayed relative to younger individuals.

Finally looking at education we find that, in accordance with Hypothesis 3a, individuals with less than an upper secondary education were overall more vulnerable relative to those with an upper secondary level of education as they had greater odds of being unemployed. Additionally, tertiary educated individuals were initially less vulnerable than those with an upper secondary level of education. Individuals with less than an upper secondary level of education were around 5.4 times more likely to be unemployed while tertiary educated individuals were 2.7 times less likely. As for differences in vulnerability over time – Hypothesis 3b – individuals with less than an upper secondary level of education did indeed become more vulnerable over time. Their odds of being unemployed increase by approximately 20% over a year. There is however no notable difference in change over time between the upper-secondary and tertiary levels.

6.6 Discussion & Conclusion

This chapter investigated trajectories of vulnerability to unemployment in the UK and Switzerland during the Great Recession. Using latent growth curve models, we focused on individuals' latent risk of experiencing unemployment and differences in trajectories in relation to their sociodemographic characteristics. Thus, instead of focusing on differences in labour market outcomes at the aggregate level, we model individual trajectories of vulnerability to unemployment and see how individuals' employment situation and sociodemographic characteristics influence these trajectories.

In the case of Switzerland we find that, overall, vulnerability to unemployment following the crisis was low and that it remained relatively stable over time. However, there was an increasing trend in the case of our reference group of males, aged between 35 and 44, who were employed in 2007, and with an upper secondary level of education. By contrast, vulnerability to unemployment in the UK decreased over time and this was also the case for the reference group. Additionally, inter-individual heterogeneity in the evolution of vulnerability over time is minimal in Switzerland once the covariates are taken into account, but this is not the case for the UK.

Another difference between Switzerland and the UK is related to the change in vulnerability over time in relation to individuals' employment situation. While in both countries individuals who were out of employment in 2007 were overall more likely to be unemployed, in Switzerland these individuals became less vulnerable over time relative to individuals who were employed. This isn't the case in the UK, where there was no real change in vulnerability for those not in employment.

	Sex		**Age**		**Education**	
	Level Hyp. 1a	**Change** Hyp. 1b	**Level** Hyp. 2a	**Change** Hyp. 2b	**Level** Hyp. 3a	**Change** Hyp. 3b
Switzerland	×	×	✓	×	×	×
United Kingdom	✓	×	✓	✓	✓	✓

Table 6.3 – Hypotheses by Country

As for sociodemographic differences, we find that in Switzerland women were overall more vulnerable than men as they had higher chances of being unemployed leading us to reject Hypothesis 1a. This seems to go against macro-level evidence suggesting that the crisis affected men more negatively than women (Keeley and Love 2010; Pissarides 2013). Nonetheless, in the case of the UK women were less vulnerable than men and thus Hypothesis 1a isn't rejected in this case.

Looking at change over time, Hypothesis 1b is rejected for Switzerland and the UK. In Switzerland, it was women who became less vulnerable over time relative to men as their chances of being unemployed dropped. In the UK, there was no significant difference between men and women in the change of vulnerability over time even if there would appear to be a slight trend towards women becoming more vulnerable. This would suggest that there weren't any real differences between men and women in coping with the crisis in the UK, but not in Switzerland.

As for differences between age groups, we find that those in the youngest age group were overall more vulnerable than middle-aged individuals in both the UK and Switzerland and thus Hypothesis 2a isn't rejected for either country. This result is expected as generally younger individuals are more likely to become unemployed especially in times of economic crisis (Russell and O'Connell 2001; Keeley and Love 2010).

However, where there is a difference is change over time. While in Switzerland there seems to be no significant difference between age groups in the change of vulnerability over time, in the UK we find that the youngest – 18–24 – become less vulnerable over time relative to 35–44-year-olds. Thus, Hypothesis 2b is rejected in the case of Switzerland but not for the UK. This would suggest that individuals who were younger at the time the crisis occurred were somewhat able to recover.

However, another interesting result in the case of the UK is how individuals in the 45+ group became more vulnerable over time as their chances of experiencing unemployment. This result also holds even when taking into account the level of education. This could possibly be related to a delayed effect of the crisis for this age group relative to younger individuals.

Finally, in the case of Switzerland there seems to be no significant difference in vulnerability to unemployment overall or over time between the different educational groups which leads us to reject Hypotheses 3a and 3b for Switzerland.

In the case of the UK, there is a clear difference in the overall level of vulnerability between educational groups. Individuals with less than an upper secondary level of education were overall more vulnerable while those having completed tertiary-level education were less vulnerable relative to the upper secondary level reference group thus supporting Hypothesis 3a. Moreover, lower educated individuals became more vulnerable over time as they became more likely to be unemployed relative to other groups providing evidence in support of Hypothesis 3b. This suggests that individuals with low levels of education were less able to cope with the consequences of the crisis. Additionally these results are in line with macro-level data suggesting that the 2008 Financial Crisis more strongly affected lower educated individuals (Gregg and Wadsworth 2010).

Comparing Switzerland and the UK, the main difference between the two is the overall direction of change in vulnerability which is decreasing in the UK and increasing in Switzerland. This may in part be due to a delayed response to the financial crisis and ensuing recession by the Swiss labour market. We also find that educational differences are more pronounced in the UK while differences between sexes are more marked in Switzerland.

However, these results should be interpreted with caution. First, they are based self-reported employment information measured annually and not on register data. Second, as with all panel data, there is the problem of attrition. While, full-information maximum likelihood can somewhat reduce bias due to missingness in MCAR and MAR situations (Enders 2001) we should still be wary of attempting to generalize these results especially in the case of labour market status. Third, the choice of a linear latent growth curve model while simplifying the estimation and interpretation of the models, may prevent us from capturing non-linear time trends in vulnerability to unemployment. However, exploratory analyses with quadratic models yielded some estimation problems especially in the case of Switzerland as the proportion of individuals who were unemployed was relatively low. The general trends were similar although differences between individual trajectories over time in relation to sociodemographic characteristics were unclear.

In conclusion, using latent growth curve models we were able to estimate trajectories of vulnerability to unemployment in the medium term for Switzerland and the United Kingdom. We found that in Switzerland, the main difference between individuals was in the level of vulnerability but not its change over time while in the UK there were differences in change over time according sex, age, and education. Latent growth curve models are therefore a promising method for studying trajectories in a holistic perspective when the latent construct is thought to be quantitative as is the case with vulnerability to unemployment. However, while this methods is able to capture overall trends, further analysis is needed to understand the underlying dynamics of these trends. In the case of Switzerland for instance, there is an overall increasing trend of vulnerability, but this could be due to a delayed effect of the crisis or a tendency for those entering unemployment to remain there. Other methods such as event history analysis can be used to investigate the dynamics behind changes in vulnerability to unemployment over time. Nevertheless this application demonstrated the usefulness of latent growth curve models to investigate trends in the change in vulnerability to unemployment in the medium term in a holistic perspective.

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6.A Descriptive Statistics

6.A.1 Switzerland

	Employed	**Unemployed**
2008	3128 (98.3%)	53 (1.7%)
2009	2895 (97.8%)	64 (2.2%)
2010	2895 (97.9%)	61 (2.1%)
2011	2867 (98.3%)	51 (1.7%)
2012	2748 (99.0%)	29 (0.9%)
2013	2611 (98.2%)	48 (1.8%)
2014	2477 (98.1%)	49 (1.9%)
2015	2415 (98.5%)	38 (1.5%)

Table 6.A.1 – Descriptive statistics for employment status (dependent variable)

Employment status	
Employed	3304 (89.7%)
Unemployed	67 (1.8%)
Out of labour force	314 (8.5%)
Sex	
Male	1669 (45.3%)
Female	2016 (54.7%)
Age	
18–24	543 (14.7%)
25–34	629 (17.1%)
35–44	1263 (34.3%)
45+	1250 (33.9%)
Education	
Less than upper secondary	383 (10.4%)
Upper secondary	1955 (53.1%)
Tertiary	1347 (36.6%)

Table 6.A.2 – Descriptive statistics for covariates (measured in 2007)

6.A.2 UK

	Employed	**Unemployed**
2008	6008 (95.1%)	307 (4.9%)
2010	4893 (92.9%)	373 (7.1%)
2011	4533 (93.2%)	333 (6.8%)
2012	4171 (93.5%)	291 (6.5%)
2013	3992 (94.0%)	256 (6.0%)
2014	3711 (93.8%)	245 (6.2%)
2015	3510 (93.7%)	235 (6.3%)

Table 6.A.3 – Descriptive statistics for employment status (dependent variable)

Employment status	
Employed	6053 (85.8%)
Unemployed	246 (3.5%)
Out of labour force	759 (10.8%)
Sex	
Male	3325 (47.1%)
Female	3733 (52.9%)
Age	
18–24	1160 (16.4%)
25–34	1844 (26.1%)
35–44	2316 (32.8%)
45+	1738 (24.6%)
Education	
Less than upper secondary	913 (12.9%)
Upper secondary	3460 (49.0%)
Tertiary	2685 (38.0%)

Table 6.A.4 – Descriptive statistics for covariates (measured in 2007)

6.B Model Information Criteria

	Log-likelihood	AIC	BIC	Nb. params	*N*	Corr. factor	χ^2 diff.	*df*	*p*
Model 0	-1767.361	3544.723	3575.783	5	3685	0.962			
Model 1	-1691.587	3401.175	**3457.083**	9	3685	1.015	140.108	4	< 0.000
Model 2	-1687.933	3397.866	3466.198	11	3685	1.015	7.213	2	0.027
Model 3	-1673.826	**3381.651**	3487.256	17	3685	1.003	28.752	6	< 0.000
Model 4	-1670.103	3382.206	3512.658	21	3685	1.004	7.404	4	0.116

Table 6.B.1 – Information Criteria SHP Models
Minimum in bold; χ^2 difference calculated according to
`https://www.statmodel.com/chidiff.shtml` using log-likelihood

	Log-likelihood	AIC	BIC	Nb. params	*N*	Corr. factor	χ^2 diff.	*df*	*p*
Model 0	-5296.286	10602.57	10636.88	5	7058	1.184			
Model 1	-4734.056	9486.112	9547.869	9	7058	1.063	1232.961	4	< 0.000
Model 2	-4721.975	9465.951	9541.432	11	7058	1.056	23.546	2	< 0.000
Model 3	-4705.322	9444.643	9561.296	17	7058	1.053	31.838	6	< 0.000
Model 4	-4614.024	**9270.049**	**9414.149**	21	7058	1.030	195.379	4	< 0.000

Table 6.B.2 – Information Criteria Combined BHPS & UKHLS Models
Minimum in bold; χ^2 difference calculated according to
`https://www.statmodel.com/chidiff.shtml` using log-likelihood

Chapter 7 Employment Transitions in the UK and Switzerland

7.1 Introduction

Starting in the 1970s – but especially since the 1990s – there has been an increasing proliferation of precarious forms of work characterized by (unwanted) part-time employment, fixed-term contracts, low job security, low pay, and poor or dangerous working conditions (Goos and Manning 2007; Kalleberg 2009; Standing 2011).

While the effects of the 2008 Financial Crisis and the ensuing Great Recession on unemployment are clear, the effects of the crisis in relation to precarious employment are far more uncertain (Gallie and Ying 2013). There is some evidence that stable jobs were replaced with more unstable ones in the aftermath of the crisis (Leschke et al. 2012). However the impact of the crisis in general, and especially, on the labour market varies substantially between countries especially within Europe (Lallement 2011).

This chapter proposes an original multidimensional and longitudinal approach to modelling transitions to and from precarious forms of employment that combines latent class analysis (LCA) with dynamic panel models for categorical data using longitudinal panel studies. LCA allows us to combine multiple objective (categorical) indicators in order to create different classes of precarious and non-precarious employment and thus employ a multidimensional approach. The dynamic panel models then allow us to model transitions between these different classes over time in relation to individuals' previous situation and characteristics. The aim is to identify whether individuals were more likely to transition to precarious employment in the aftermath of the 2008 Financial Crisis, and which sociodemographic groups were most affected in the United Kingdom and Switzerland.

We also employ our combination of LCA and dynamic panel models in two different contexts which allows us to investigate how it behaves in different situations. On the one hand, Switzerland was relatively unaffected by the crisis. On the other, the UK was among the first countries affected by the crisis even if other European countries were subsequently more negatively affected than the UK. Thus we can compare two countries that vary both in their labour markets and in the consequences of the 2008 Financial Crisis on employment.

7.2 Defining Precarious Employment

Precarious employment (or precarious forms of employment) doesn't have a clear definition. Generally, it is defined in relation to the contractual employee–employer relationship, and employees' working conditions. The major differences are related to the indicators chosen (objective, subjective, or a combination thereof) to measure the different dimensions, whether precarious employment is measured at the individual or aggregate level, and whether precarious employment is thought of as a stage that can lead to further social exclusion.

In the case of the UK, there is a parliamentary policy statement defining vulnerable workers as: "[...] someone working in an environment where the risk of being denied employment rights is high and who does not have the capacity or means to protect themselves from that abuse. Both factors need to be present. A worker may be susceptible to vulnerability, but that is only significant if an employer exploits that vulnerability." (DTI 2006, 25) According to this definition, workers are only vulnerable if they are unable to defend their employment rights *and* their employer denies them those rights.

However, this is not the case for most definitions (ILO 1999, 2013; Paugam 2007; Leschke and Watt 2008a, 2008b; Pollert and Charlwood 2009; Standing 2011; Leschke et al. 2012) which instead take the opposite approach by considering precarious employment as being a situation in which an individual is simply *at risk* of being exploited by their employer.

There are many approaches to measuring precarious employment (see Muñoz de Bustillo et al. 2011, Findlay et al. 2013, Ritschard et al. 2018 for overviews), but generally the indicators used to identify precarious employment are broadly similar whether the analysis is at the macro or individual level. Most definitions of precarious employment focus on similar aspects which are usually the employer–employee relationship (contract type, working hours), wages, collective interest representation, workplaces' physical environment, and working conditions (work–life balance, satisfaction, subjective job security, opinion on future job prospects, work experience, employment trajectories or careers).

The multidimensionality of precarious employment also poses methodological challenges. Beyond the choice of indicators, there is the issue of which methods should be used to combine them. Generally, most of the macro-level approaches use additive models with possibly some weighting (Leschke and Watt 2008a, 2008b). Another possibility is multiple correspondence analysis as employed by Paugam (2007). In this chapter we will employ objective indicators of precarious employment – employment status, wages, contract type, working hours – principally relating to the employer–employee relationship and construct a typology of employment situations using LCA. This method allows us to create classes of employment based on categorical indicators. The advantage of using LCA over other methods is that it takes into account potential measurement error in the estimation as well as providing methods to test different class specifications.

Regardless of how precarious employment is conceived or measured, at the individual level there is evidence that precarious forms of employment are more prevalent within certain social groups, in certain countries, and welfare regimes (Kalleberg et al. 2000; McGovern et al. 2004; Kalleberg 2012; Green et al. 2013; Holman 2013). Women for instance, are more likely to hold part-time jobs or have non-standard forms of employment than men. Consequently, women are also more likely to have jobs with fewer benefits, or of lower quality than men. The same is true for younger workers, but also for older workers, and especially those close to retirement age, who are more likely to be in more precarious forms of employment (i.e. to have "bad" jobs) especially after entering unemployment later in life. Education also plays a role as individuals with higher levels of education are less likely to have bad jobs. As a result, the chances of being in precarious employment are not evenly distributed among different sociodemographic groups.

7.3 Precarious Employment and the Crisis

The effects of the crisis on the prevalence of precarious forms of employment is unclear, and there are competing views on its effects. A first view is that the increase in unemployment caused by the crisis disproportionately affected individuals in poor quality jobs. Consequently there would be an increase in the overall level of job quality as those remaining in employment would have higher quality jobs. Alternatively, it is possible that the crisis presented an opportunity for employers to stop focusing on job quality altogether as the priority for governments became to stem rising unemployment through the creation of jobs regardless of their quality. In this case, the overall level of job quality would decrease. Another view is that there is an increasing polarization of the labour market between those in more exposed and precarious jobs, and individuals in more secure core sectors. The crisis therefore is thought to possibly exacerbate this division (Gallie and Ying 2013, 117) meaning that job quality in less protected sectors would decrease more sharply than job quality in more protected sectors.

There is some evidence supporting an overall increase in job quality in the aftermath of the crisis. Using data from the European Labour Force Surveys and a single indicator, job control, Gallie and Ying (2013, 123–127) find that individuals in low quality jobs (manual occupations) were more likely to become unemployed most notably Southern European or Transition (Eastern European) countries. This suggests that there may have been an apparent increase in overall job quality as a result of rising unemployment in these countries. In addition, they find little evidence of a decrease in job quality for those who remained employed. At the aggregate level, Leschke et al. (2012, 22) find that, within the EU, there wasn't an overall marked decline in the European Trade Union Institute's (ETUI) job quality index with a few exceptions.

However, when focusing on more objective indicators, such as contract types or working hours there is more evidence of a decline in job quality after the crisis. Curci et al. (2012) look at the impact of the crisis on three different job quality indicators: contract status and stability (informal work, part-time or temporary employment, etc.), willingness to continue working in the same job, and wages. They find that following the crisis, there was an increase in most developed countries in the incidence of part-time and temporary employment, and this is true for both the UK and Switzerland. More crucially, the proportion of involuntary part-time or temporary employment also rose following the crisis (Curci et al. 2012 do not present data for Switzerland for this indicator). In the case of Switzerland, however, it would appear that the proportion of involuntary part-time work didn't really change (OFS 2017). Similarly, Leschke et al. (2012) find that in the case of the UK and Ireland, where job quality did decline according to the ETUI's job quality index, it can be attributed to an increase in involuntary part-time work. Likewise, Curtarelli et al. (2014) find that main change in relation to job quality in the UK was a decrease in the amount of individuals working more than 36 hours per week.

Looking at Figure 7.1, we can see that there was a slight rise the share of part-time employment in the UK immediately after the crisis. However, it does decline to almost pre-crisis levels by 2018. On the other hand, in Switzerland there is a continuous upward trend starting before the crisis, with there actually being a small dip immediately after 2008. In both countries, this data suggests that the 2008 Financial Crisis had a relatively small effect on trends in part-time employment.

As for temporary employment, i.e. individuals with limited-duration employment contracts, Figure 7.2show that there was a slight dip in the UK around 2008 before a return to levels similar to those before the crisis. This could imply that individuals with limited-duration contracts were more likely to become unemployed during this period. In Switzerland, the trend is towards an overall increase. However, it occurs much later, around 2014, and then plateaus later. This data suggests that in terms of part-time employment, the crisis didn't really have much an effect relative to the trends observable prior to the 2008 Financial Crisis. However, things are slightly less clear when it comes to limited-duration contracts as in the UK there is a noticeable dip around 2008–2009 while in Switzerland, there is a noticeable increase, after a small increase around 2008–2009, much later nearly six years after the beginning of the crisis.

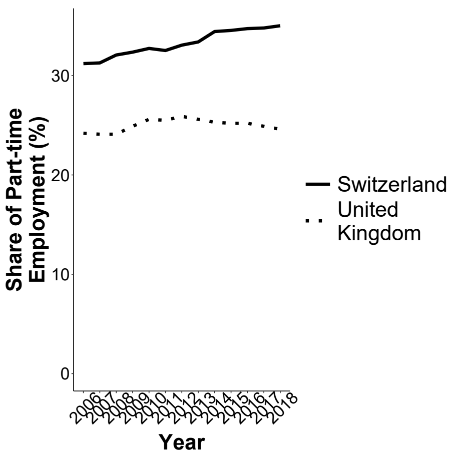

Figure 7.1 – Share of Part-time Employment in UK and Switzerland; Sources: Eurostat and Swiss Federal Statistics Office

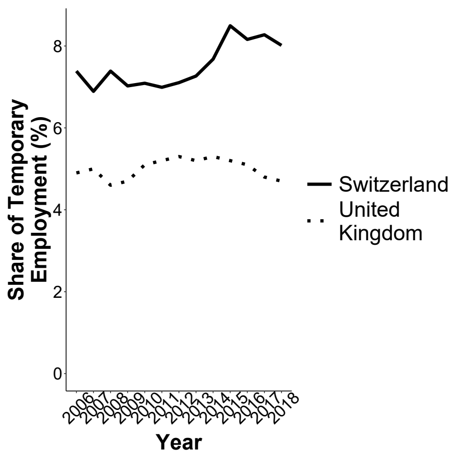

Figure 7.2 – Share of Temporary (Limited-duration Contract) Employment in UK and Switzerland; Sources: Eurostat and Swiss Federal Statistics Office

What this data suggests is that immediate consequences of the crisis on job quality are not straightforward. In the UK, the prevalence of part-time work increased suggesting a worsening of conditions, but the share of jobs with limited-duration contracts decreased while the opposite is true in Switzerland. This shows the necessity of taking into account multiple indicators as it is possible to the come to the conclusion that job quality decreased in the UK when looking at part-time employment, but that job quality increased due to the drop in temporary contracts.

Contrary to the analysis strategy adopted in this chapter, all the analyses performed at the macro-level use repeated cross-sectional data and, with the exception of Leschke et al. (2012), look at specific components of job quality rather than employing multidimensional constructs. Moreover – with the exception of Gallie and Ying (2013) – most studies do not inform us on whether individuals in stable employment remained there, or whether individuals who experienced unemployment after the crisis had to move to precarious employment. We can nevertheless make two hypotheses concerning transitions to precarious employment following the crisis:

Hypothesis 1 Compared to the period before the crisis, individuals who were in stable employment became more likely remain in stable employment rather than end up in another labour market position.

Hypothesis 2 Compared to the period before the crisis, individuals leaving unemployment will be more likely to end up in precarious employment.

Reframing the above hypotheses, Hypothesis 1 posits that job quality increased as the crisis led individuals in the higher quality jobs to end up less likely to end up in lower quality positions. Hypothesis 2 posits a decline in job quality but through an indirect path whereby individuals who lost their jobs in the crisis would subsequently end up in lower quality jobs.

Looking at individual transitions using longitudinal panel data, we can model the chances of employees moving between different forms of employment in relation to their characteristics which cannot be done with aggregate data. To achieve this, we combine latent class analysis (LCA) with a dynamic (auto-regressive) multinomial logistic regression with a random person-specific intercept. Additionally, we also consider the case of unemployment as another state to which individuals can transition to see if precarious employment occurs after a spell of unemployment. Rather than leading individuals directly into less secure forms of unemployment, the crisis may have increased the likelihood of individuals first entering unemployment and then subsequently becoming more likely to re-enter employment by taking more precarious jobs.

7.4 Data

We use data from two panel studies in the UK and one in Switzerland. The Swiss data comes from the Swiss Household Panel (SHP) (Tillmann et al. 2016) and the UK data comes from the British Household Panel (BHPS) and its successor study Understanding Society: the UK Household Longitudinal Study (UKHLS) (University of Essex, Institute for Social and Economic Research et al. 2019). We look at transitions in employment statuses between 2005 and 2012 which corresponds to eight waves of data. However, the BHPS ended in 2008 and its participants were not invited to join the UKHLS until 2010. Thus, we only have seven waves of data in the case of the UK as there is no data available for BHPS participants in 2009.

The Swiss sample comprises 3,173 individuals (15,745 observations) aged between 20 and 50 in 2005 who were employed or unemployed, and the UK sample comprises 6,424 individuals (23,310 observations) also aged between 20 and 50 in 2005 who were employed or unemployed.

7.4.1 Indicators of Precarious Employment

Based on the definitions and approaches presented in Section 7.2, the main dimensions of precarious employment are the type of employment contract, working hours, wages, interest representation, workplace conditions, and opportunities for career advancement and development. However, not all of these dimensions have available indicators in the SHP, BHPS, and UKHLS. The following indicators were used as they are assessed with the same, or very similar questions, on a yearly basis in all surveys: gross hourly wage (approximated from gross monthly wage), contract type (fixed-term vs. unlimited duration), part-time work, and employment status (employed vs. unemployed). As LCA creates latent categories from categorical variables, gross hourly wage was recoded into two categories: below two thirds of the median gross hourly wage in 2008 or above it. The median gross hourly wage was approximated from the median gross monthly wage for Switzerland in 2008 (5,823 Swiss francs (OFS 2019)), and from the median gross weekly wage for full-time employees in the UK in 2008 (479 British pounds (ONS 2008)).

We focus on these objective indicators of precarious employment related to the employer–employee relationship for three reasons. Firstly, these indicators are common to most definitions of precarious employment. Secondly, it makes it easier to compare two different countries as they are more reliable than subjective indicators. The questions used to assess these aspects of individuals' employment situation enable a more reliable comparison across surveys contrary to questions relating to subjective appreciations of employment which have different response scales, or different wording. Finally, many subjective indicators, and even certain objective indicators, are not measured annually in either the SHP or the UKHLS which would further reduce the number of data points available and make modelling transitions more problematic as even with annual data there is most likely an underestimation of transitions between employment statuses.

7.5 Methods

In this chapter we combine two methods in order to investigate employment transitions in order to tackle two distinct issues: dealing with the multidimensional nature of precarious employment, and the dynamic nature of employment transitions which are often dependent on individuals' previous position. The solution proposed here is to combine LCA with dynamic longitudinal panel models. LCA allows us to deal with the multidimensional nature of precarious employment while dynamic longitudinal panel models can be employed to model transitions while dealing with (time-constant) unobserved heterogeneity and the initial conditions problem when employing suitable model specifications (Wooldridge 2005; Rabe-Hesketh and Skrondal 2013; Skrondal and Rabe-Hesketh 2014). The advantage of combining these two methods is that it allows us to use observation-level variables which is not the case with most multivariate latent models, and it allows a more flexible specification of the transition model than when simultaneously estimating the latent class and transition models as in the case of latent transition analysis (LTA). It also allows for estimating models with a large number of time points as using a joint model becomes exponentially more difficult to estimate as more time points are added (Collins and Lanza 2010, 189).

There are nevertheless a few difficulties that need to be taken into account when combining these two methods in our particular case. Firstly, it is not possible to reuse individual latent class assignments directly. LCA is a method for identifying categorical (nominal) latent variables from a series of manifest or observed categorical indicators; in other words, it is a method to classify individuals' responses to a series of indicators into similar groups. However, measurement error needs to be taken into account when assigning individuals to a latent class on the basis of the estimated model. There are different solutions available for this issue which will be presented in Section 7.5.1. Secondly, to properly interpret movements between employment statuses over time in the subsequent dynamic model, we need to ensure that our latent classes are the same over time. We therefore estimated the latent classes for each time point jointly and imposed equality constraints to ensure that the items measured the same latent variables over time.

7.5.1 Latent Class Analysis

LCA is used to model latent categorical variables that are measured using categorical indicators (see Table 4.1 in Chapter 4). As we saw in Section 4.2, the idea is to categorize individuals into different latent classes based on their response patterns to a set of categorical indicators. Individuals with similar probabilities of producing the same response vector are put into the same class with the idea of having as much separation as possible between classes i.e. minimizing the overlap between classes. In practice, classes usually overlap to some degree and individuals often have non-zero probabilities of belonging to multiple classes. The number of classes to be used, however, is determined a priori. Determining which number of classes best fits the data is usually done using absolute or relative model fit criteria (Collins and Lanza 2010, 82; McCutcheon 2002, 66), but can also be determined in accordance with a theoretical model.

As shown in Equation (4.47) in Section 4.2.1, a latent class model can be expressed mathematically as follows (Collins and Lanza 2010, 41):

$$P(\mathbf{Y} = \mathbf{y}) = \sum_{c=1}^{C} \gamma_c \prod_{j=1}^{J} \prod_{r_j=1}^{R_j} \rho_{j,r_j|c}^{I(y_j=r_j)} \tag{7.1}$$

This expression shows that latent class models estimate the probability of observing a vector $\mathbf{y}$ of responses. This vector is of length J which is the number of y_j manifest indicators which we want to group into latent classes. This probability is determined by the probability of belonging to each of the C latent classes – γ_c – also called the latent class *prevalences*. The second part of the expression shows us that this probability depends on the conditional probabilities for each response category of each indicator $\rho_{j,r_j|c}$ also called *item-response* probabilities. An item-response probability is the probability of responding a certain response category r_j of a manifest indicator y_j conditional on being in a certain latent class c. This model assumes *local independence*, that is that the item-response probabilities are independent conditional on latent class membership. In other words, we assume that our indicators are only associated due to being components of the same latent class. Finally, the indicator function $I(y_j = r_j)$ serves to select the correct item-response probabilities to multiply together.

Latent Class Membership Assignment

The first step in assigning an individual to a latent class is to calculate the posterior probability of belonging to a latent class. Individual posterior probabilities are calculated on the basis of the item-response probabilities and the latent class prevalences. This can be expressed as (Collins and Lanza 2010, 69):

$$P(L = c_i|\mathbf{Y} = \mathbf{y}) = \frac{\left(\prod_{j=1}^{J}\prod_{r_j}^{R_j}\rho_{j,r_j|c_i}^{I(y_j=r_j)}\right)\gamma_{c_i}}{\sum_{c=1}^{C}\gamma_c\prod_{j=1}^{J}\prod_{r_j=1}^{R_j}\rho_{j,r_j|c}^{I(y_j=r_j)}} \qquad (7.2)$$

The numerator is the probability of observing a given response vector $\mathbf{y}$ for a specific latent class $L = c_i$ while the denominator is the probability of observing a given response vector $\mathbf{y}$ across *all* latent classes and is identical to Equation 7.1.

After calculating the individual posterior probabilities of belonging to each latent class, an assignment method needs to be chosen. As was discussed in Section 4.2.1, the most common methods are modal, proportional, and random assignment (Goodman 2007; Vermunt 2010). In general, it is likely that individuals will have non-zero predicted class membership probabilities for more than one latent class due to measurement error. Consequently, when reusing class assignments in subsequent (regression) analyses, classification uncertainty needs to be taken into account. When this isn't done, in the case of a regression of the class assignment on other covariates, the coefficients are often downwardly biased. One possible solution it the use of correction procedures which take into account classification uncertainty or error (Bolck et al. 2004; Collins and Lanza 2010, 68; Vermunt 2010; Asparouhov and Muthén 2014). An alternative procedure is to do multiple random draws for each individual based on the posterior distribution of the class membership probabilities – "pseudo-class draws" – and then estimate a model for each draw. The regression estimates relating latent classes to covariates are then pooled according to Rubin's (1987) rules for multiple imputation (Bandeen-Roche et al. 1997; Bray et al. 2015). This is the approach we adopt.

Results

The LCA models were estimated in Mplus 7.4 (Muthén and Muthén, 1998–2015). The estimated item-response probabilities, corresponding to the $\rho_{j,r_j|c}$ term in Equation 7.1 are presented in Table 7.1 and the estimated latent class prevalences, corresponding to the γ_c term in Equation 7.1, for each year are available in Tables 7.A.1 and 7.A.2 for Switzerland and the UK respectively. We chose to estimate an LCA model with three classes on the basis that the interest was to contrast three different possible labour market states: unemployment, precarious employment, and stable employment.

	Switzerland			*UK*		
	Unemployed	*Unstable*	*Stable*	*Unemployed*	*Unstable*	*Stable*
Employment status						
Employed	0.000† (——)	1.000† (——)	1.000† (——)	0.000† (——)	1.000† (——)	1.000† (——)
Unemployed	1.000† (——)	0.000† (——)	0.000† (——)	1.000† (——)	0.000† (——)	0.000† (——)
Work Hours						
Full-time	0.000† (——)	0.397 (0.016)	0.589 (0.015)	0.000† (——)	0.637 (0.009)	0.853 (0.004)
Part-time	0.000† (——)	0.603 (0.016)	0.411 (0.015)	0.000† (——)	0.363 (0.009)	0.147 (0.004)
Missing	1.000† (——)	0.000† (——)	0.000† (——)	1.000† (——)	0.000† (——)	0.000† (——)
Contract Type						
Open-ended	0.000† (——)	0.825 (0.010)	0.992 (0.011)	0.000† (——)	0.954 (0.003)	0.958 (0.002)
Fixed-term	0.000† (——)	0.175 (0.010)	0.008 (0.011)	0.000† (——)	0.046 (0.003)	0.042 (0.002)
Missing	1.000† (——)	0.000† (——)	0.000† (——)	1.000† (——)	0.000† (——)	0.000† (——)
Wages						
Good pay	0.000† (——)	0.697 (0.041)	1.000† (——)	0.000† (——)	0.000† (——)	1.000† (——)
Low pay	0.000† (——)	0.303 (0.041)	0.000† (——)	0.000† (——)	1.000† (——)	0.000† (——)
Missing	1.000† (——)	0.000† (——)	0.000† (——)	1.000† (——)	0.000† (——)	0.000† (——)

Table 7.1 – Item Reponse Probabilities
† indicates constrained probabilities; Std. errors in brackets
Data Sources: Swiss Household Panel, British Household Panel Study, UK Longitudinal Household Study

In the case of longitudinal analyses using latent classes, the item-response probabilities (analogous to emission probabilities in hidden/latent Markov models) for each class are constrained to be equal across measurements to make sure that the classes can be interpreted in the same manner across time (Collins and Lanza 2010, 194). By design, the first class contains only individuals who are unemployed, and therefore who provided no information on indicators other than employment status. As such, the item-response probabilities for providing missing information for the other indicators are constrained to one for this class. Conversely, for the other two classes, the probability of missing information is constrained to zero for indicators other than employment status with the other probabilities being freely estimated. For the two employment classes, we used the item-response probabilities to assign the labels.

Looking at the item-response probabilities for the two employment classes, we find broadly similar patterns in the case of the UK and Switzerland. In both countries the unstable class is characterized by having a higher probability of individuals having comparatively low wages (less than two thirds of the median hourly wage in 2008). The unstable class is also characterized by a higher probability of individuals being in part-time employment though the difference is not particularly marked. As for the type of employment contract, there is no difference between the stable and unstable employment classes in the UK. For Switzerland, the probability of having a fixed-term contract is higher for the unstable class but it is still relatively low.

The latent class prevalences (Tables 7.A.1 and 7.A.2 in the Appendix of this chapter) give us an idea of the overall change in the prevalence of precarious employment over time. In the case of both the UK and Switzerland, there is a decline in the proportion of individuals in unstable employment over time in our samples while the proportion of individuals in unemployment remains relatively stable.

7.5.2 Dynamic Panel Models for Categorical Data

As we are interested in modelling transitions between our different labour market statuses, we opt for a dynamic panel model which allows for modelling autoregressive processes. As was discussed in Section 4.3, adopting a “naive” estimation technique which doesn’t take into account initial conditions and unobserved heterogeneity leads to biased results especially in the case of short panels when including the lagged dependent variable as a covariate. Wooldridge (2005) proposes a simple solution in the case of random effects models with categorical outcomes that allows for handling the initial conditions problem. The initial conditions problem (cf. Section 4.3.2) refers to the issue of the initial observation of the dependent variable not being the initial observation for the underlying process. This simple solution reduces the bias of the “naive” technique by accounting for endogeneity in relation the initial response, and in relation to the covariates.

Here we use the modified solution proposed by Rabe-Hesketh and Skrondal (2013) which performs just as well Wooldridge’s method, but allows for unbalanced data i.e. with gaps in measurement. We combine their solution, more particularly their “Model P” specification (Rabe-Hesketh and Skrondal 2013, 347; Equation 8) which includes the means of time-varying variables as well as their initial values, with a multinomial logistic regression model with random intercepts and robust standard errors.

In other words, we estimate a multinomial logistic regression model with individual-specific initial values and means for time-varying variables, the initial observation of the dependent variable for each individual, and separate random effects for each combination of outcomes relative to the reference category of the dependent variable. Having separate random effects rather than single shared one is preferable as it means that the model is structurally equivalent regardless of the reference category that is chosen (Hartzel et al. 2001). This also allows the assumption of "independence of irrelevant alternatives" which underpins multinomial logistic regression to be somewhat relaxed (Hedeker 2003, 1443; Grilli and Rampichini 2007, 384; Steele et al. 2013, 705). Our transition model can therefore be expressed as:

$$y^*_{itr} = \mathbf{x}'_{it}\boldsymbol{\beta}_r + \rho_r y^*_{i(t-1)r} + \overbrace{\alpha_r + \rho_0 y^*_{i0} + \mathbf{x}^{*\prime}_{i0}\boldsymbol{\beta}_{0r} + \bar{\mathbf{x}}'_i\boldsymbol{\beta}_{\bar{x}r} + u_{ir}}^{c_{ir}} + \epsilon_{itr} \tag{7.3}$$

where $y^*_{itr} = \log\left(\frac{\pi_{itr}}{\pi_{itR}}\right)$, r designates a response category of the dependent variable, i the individual, t the time point, and R the reference category. π_{itr} is the probability of responding r at t and π_{itR} the probability of responding the reference category R. In our case y^*_{itr} represents the log-odds of being in one latent class relative to the reference latent class. $\mathbf{x}'_{it}$ contains the values of the exogenous time-varying covariates at t, $\mathbf{x}^{*\prime}_{i0}$ contains the values of the time-varying covariates at the first measurement as well as any time-constant covariates, $\bar{\mathbf{x}}'_i$ contains the means of the time-varying covariates, and u_{ir} is an individual- and response-specific error term. Time-constant unobserved heterogeneity is captured by the terms comprising c_{ir}.

The c_{ir} term is supposed to capture two aspects of endogeneity. The first is the initial conditions problem which refers to the problem of estimating dynamic models for individuals after the process of interest has already begun. The assumption that the state in which we initially observe individuals is exogenous is often not realistic. Consequently, the state in which we initially observe an individual is dependent on unobserved heterogeneity captured by the random person-specific intercept u_{ir}, and the state an individual was in prior to first being observed (Skrondal and Rabe-Hesketh 2014, 212). This is controlled for by the $\rho_0 y^*_{i0}$ term which explicitly includes the initial response as a covariate. The second aspect of endogeneity is between-subject confounding, or level 2, endogeneity. Between-subject confounding refers to the problem of the individual random intercept – u_{ir} which is supposed to account for omitted time-constant covariates – not being independent of the covariates in the model. This is done by including the individual-specific means for time-varying covariates as controls (Skrondal and Rabe-Hesketh 2014, 227).

Finally, we also have to take into account the uncertainty related to the assignment of individuals to latent classes. To do this, we perform 20 pseudo-random class draws and then estimate the dynamic panel model for each draw. The estimates are then aggregated using Rubin's (1987) rules as in the case of multiple imputation.

Results

The dynamic panel regression model was estimated in Stata 14 (StataCorp 2015). While we have an unbalanced panel design, the improved Wooldridge (2005) solution by Rabe-Hesketh and Skrondal (2013) allows for unbalanced data and therefore all complete observations provided by an individual are included.

Switzerland The results of the dynamic models are presented in Tables 7.2 and 7.3. The estimates for the additional controls relating to the initial conditions and unobserved heterogeneity, that is the c_{ir} term in Equation 7.3, are in Tables 7.B.3 and 7.B.4 in the Appendix. In the first model we include the lagged dependent variable in addition to individuals' sociodemographic characteristics and a crisis dummy (2005–2008 vs. 2009–2012). Age and the crisis dummy are time-varying variables while education and sex are time-constant. We include interactions with the crisis dummy variable in a stepwise manner to evaluate whether the crisis modified the chances of transitioning between employment statuses but also the relationships with the sociodemographic variables. In terms of the hypotheses presented in Section 7.3, the main interest is on the interaction terms between the lagged dependent variable and the crisis dummy.

Looking at the simplest model without any interaction effects, for our first outcome – unemployment vs. stable employment – we find that there is a relatively strong tendency towards state dependence even when taking into account initial conditions and unobserved heterogeneity. In other terms, compared to the chances of individuals in stable employment transitioning to unemployment, those who were previously unemployed were much more likely to remain unemployed. Exponentiating the coefficient to get the odds ratio, we find that unemployed individuals were nearly six times more likely to be unemployed compared to individuals who were previously in stable employment. However, individuals previously in unstable employment were no more likely to transition to unemployment compared to individuals previously in stable employment. The only other result of note is that women are more likely to be unemployed than men. Taking the odds ratio, they were around 1.7 times more likely to experience unemployment than men. We find no associations between the odds of being unemployed relative to being in stable employment and the other sociodemographic characteristics. Additionally, there isn't any notable association between the crisis and our outcome indicating that, overall, the crisis didn't make individuals more likely to be unemployed in Switzerland.

Looking at our second outcome – unstable employment vs. stable employment – we again find evidence of state dependence as individuals in unstable employment are significantly more likely to remain in it. In fact they are approximately 25% to remain in unstable employment compared to individuals in stable employment transitioning to unstable employment. However the association is not as strong as it was in the case of unemployment. We find that women are more likely to be in unstable employment rather than stable employment. This is also the case for individuals with less than an upper secondary level of education. More interestingly, we find that the crisis decreased the chances of individuals being in unstable employment overall, as did completing tertiary-level education.

Looking at the interaction term between lagged dependent variable and the crisis dummy allows us to evaluate our results in relation to Hypotheses 1 and 2. The results show that the crisis didn't lead to any major changes in the relationship between the odds of being in unemployment or in unstable employment, and individuals' previous employment situation. As such, the crisis didn't make any category of employment more or less likely to transition to unstable employment or unemployment when comparing the pre- and post-crisis periods. Therefore, in the case of Switzerland, there is no support for either hypothesis and no evidence that the crisis modified the relationship between the individuals' previous employment situation and their subsequent labour market position.

As for sex, the interaction with the crisis dummy also suggests that the crisis didn't

	(1)	(2)	(3)	(4)	(5)
$y_{(t-1)}$ (Ref: Stable)					
Unemployment	1.762***	2.084***	1.759***	1.683***	1.754***
	(0.329)	(0.388)	(0.329)	(0.337)	(0.329)
Unstable	0.329	0.472	0.326	0.316	0.331
	(0.181)	(0.261)	(0.181)	(0.181)	(0.181)
Crisis (2009+ vs. 2005–2008)	0.210	0.405	0.459*	0.536*	0.254
	(0.153)	(0.214)	(0.211)	(0.196)	(0.192)
Female	0.550**	0.559**	0.784**	0.553**	0.552**
	(0.172)	(0.175)	(0.236)	(0.173)	(0.172)
Age (Ref: 30–44)					
under 30	0.336	0.310	0.349	0.790	0.365
	(0.561)	(0.574)	(0.565)	(0.539)	(0.564)
45+	-0.446	-0.442	-0.448	-0.280	-0.425
	(0.379)	(0.375)	(0.379)	(0.439)	(0.378)
Education (Ref: Upper sec.)					
Tertiary	-0.176	-0.176	-0.177	-0.181	-0.183
	(0.179)	(0.182)	(0.179)	(0.181)	(0.247)
Less than upper sec.	0.228	0.237	0.230	0.236	0.672
	(0.353)	(0.358)	(0.354)	(0.355)	(0.445)
$y_{(t-1)}$ (Ref: Stable) x Crisis					
Unemployment		-0.678			
		(0.437)			
Unstable		-0.230			
		(0.304)			
Female x Crisis			-0.414		
			(0.270)		
Age (Ref: 30–44) x Crisis					
under 30				-1.334*	
				(0.490)	
45+				-0.439	
				(0.290)	
Education (Ref: Upper sec.) x Crisis					
Tertiary					0.011
					(0.290)
Less than upper sec.					-0.873
					(0.572)
N			15,745		
N indiv.			3,173		

Table 7.2 – Results for Switzerland: Unemployment vs. Stable Employment
Robust std. errors in brackets; *** p < 0.001, ** p < 0.01, * p < 0.05
Data Source: Swiss Household Panel

	(1)	(2)	(3)	(4)	(5)
$y_{(t-1)}$ (Ref: Stable)					
Unemployment	0.234	0.215	0.233	0.213	0.230
	(0.168)	(0.236)	(0.167)	(0.168)	(0.168)
Unstable	0.231***	0.248***	0.230***	0.226***	0.228***
	(0.051)	(0.066)	(0.051)	(0.051)	(0.051)
Crisis (2009+ vs. 2005–2008)	-0.266***	-0.255***	-0.268***	-0.223***	-0.325***
	(0.044)	(0.056)	(0.063)	(0.062)	(0.055)
Female	0.658***	0.659***	0.657***	0.658***	0.660***
	(0.048)	(0.048)	(0.061)	(0.048)	(0.048)
Age (Ref: 30–44)					
under 30	0.188	0.189	0.188	0.275	0.193
	(0.142)	(0.142)	(0.142)	(0.149)	(0.143)
45+	-0.165	-0.165	-0.165	-0.169	-0.173
	(0.089)	(0.089)	(0.089)	(0.100)	(0.089)
Education (Ref: Upper sec.)					
Tertiary	-0.134*	-0.134*	-0.134*	-0.136*	-0.227***
	(0.049)	(0.049)	(0.049)	(0.049)	(0.064)
Less than upper sec.	0.314*	0.314*	0.313*	0.317*	0.402*
	(0.102)	(0.103)	(0.102)	(0.102)	(0.136)
$y_{(t-1)}$ (Ref: Stable) x Crisis					
Unemployment		0.042			
		(0.314)			
Unstable		-0.036			
		(0.082)			
Female x Crisis			0.002		
			(0.077)		
Age (Ref: 30–44) x Crisis					
under 30				-0.342*	
				(0.149)	
45+				-0.031	
				(0.084)	
Education (Ref: Upper sec.) x Crisis					
Tertiary					0.173*
					(0.079)
Less than upper sec.					-0.159
					(0.175)
N			15,745		
N indiv.			3,173		

Table 7.3 – Results for Switzerland: Unstable vs. Stable Employment
Robust std. errors in brackets; *** p < 0.001, ** p < 0.01, * p < 0.05
Data Source: Swiss Household Panel

modify the relationship between sex and labour market position for either pair of outcomes. However, the direct effect of the crisis for unemployment vs. stable employment is significant at the 5% level and positive indicating that once the interaction with sex is taken into account, the crisis made males more susceptible to experiencing unemployment. This is somewhat supported by the interaction term between sex and crisis which, while non-significant, is negative.

Including the interaction between the crisis dummy and age, we find that the youngest individuals, those aged under 30, became less likely to be in unemployment or unstable employment relative to stable employment. In the case of unemployment vs. employment, there is also a positive association between the crisis and the chances of being in unemployment just as in the previous model. The final set of interaction terms between education and the crisis (Model 5) shows that there was no change in the relationship between education and the likelihood of unemployment following the crisis. Moreover, the main effect of the crisis in this model is non-significant. However, in the case of unstable employment vs. stable employment, we do find that the crisis made individuals with a tertiary level of education more susceptible to being in unstable employment than previously.

The second half of Tables 7.B.3 and 7.B.4 contain the estimates for the parameters taking into account individual heterogeneity and the initial conditions. In Table 7.B.3 we see that effect of being initially unemployed is stronger than the measure of state dependence, that is the coefficient for the lagged dependent variable which measures the propensity to remain in the same state. This indicates that the initial condition is strongly linked to unobserved heterogeneity which provides evidence in favour of not using a "naive" approach omitting the initial conditions to estimate a dynamic model. We also find that a correlation between the mean of the crisis variable and unobserved heterogeneity. However, this is in part due to the fact that this variable simply corresponds to the proportion of observations for an individual that occurred after the crisis. This would therefore suggest that, in the case of unemployment vs. stable employment, there is a relationship between unobserved heterogeneity and how many times an individual was observed following the crisis. As for unstable vs. stable employment (Table 7.B.4), there is a correlation between the initial measured status and unobserved heterogeneity. However, there is only an association between the within-unit mean of age (45+) and unobserved heterogeneity in the case of the time-varying covariates. Looking at the covariance between the random effects for the two outcomes, we find a significant positive covariance which suggests that individuals who are more likely to be unemployed and are also more likely to be in unstable employment (Steele 2011, 12).

To conclude, the results for Switzerland suggest that while there is state dependence in relation to individuals' employment situation, the crisis did not change this relationship. Thus, there is no evidence to support Hypotheses 1 and 2 which posited that the crisis would modify the relationship between individuals' past labour market position and subsequent labour market outcomes. Unemployed individuals and those in unstable employment became no more or less likely to become or remain unemployed or unstably employed after the crisis than they were before it. In terms of sociodemographic characteristics, there is an indication that men were slightly more affected by the crisis in terms of unemployment if we look at the interaction term for sex in Model 3. As for the unstable employment outcome, the main consequence of the crisis was that highly educated individuals saw their chances of entering unstable employment increase.

United Kingdom For the UK, we tested the same model specifications for the dynamic panel models as we did for Switzerland. The results are presented in Tables 7.4 (unemployment vs. stable employment) and 7.5 (unstable vs. stable employment). The parameters capturing unobserved heterogeneity can be found in Tables 7.B.5 and 7.B.6 in the Appendix.

The results of the first model show that the crisis increased the overall chances of individuals being unemployed relative to being employed. Exponentiating the coefficient to get the odds ratio, we find that the chances of entering unemployment increased by nearly 50% after the crisis. In addition, we find some state dependence as individuals who were previously unemployed were more likely to remain unemployed than individuals who were previously employed. In fact, previously unemployed individuals were more than 22 times more likely to remain unemployed. This is also the case for individuals who were in unstable employment who were around 3.5 times more likely to enter unemployment compared to individual who were previously in stable employment. As for education and sex, women were less likely to be unemployed as were tertiary educated individuals. Individuals with less than an upper secondary level of education were more likely to be unemployed.

Looking at the second outcome (unstable vs. stable employment), we find similar results. The main difference is the effect of the crisis which is negative suggesting that the crisis made individuals *less* likely to enter unstable employment compared to stable employment. Individuals who were previously unemployed or in unstable employment were more likely to be in unstable employment compared to those in stable employment. Nevertheless, individuals were more likely to remain in the same employment situation suggesting a tendency towards state dependence. As for sociodemographic characteristics, the patterns are generally the same. Older individuals are more likely to be in unstable employment as are women, and individuals with less than an upper secondary level of education. Having completed tertiary education is associated with lower odds of being in unstable employment.

Adding in the interaction between the lagged dependent variable and the crisis allows us to evaluate Hypotheses 1 and 2. The results show that the crisis doesn't modify the association between individuals' previous employment state and the chances of entering unemployment. This partially invalidates Hypothesis 1 as individuals in stable employment were not more or less likely than others to experience unemployment. The rest of the associations remain broadly unchanged when compared to the first model without the interaction term.

As for the second outcome (unstable vs. stable employment), there is a significant interaction effects between the crisis and the lagged dependent variable. The crisis strengthened the tendency towards state dependence, that is the chances of remaining in the same state, in the case of unstable employment. In other words, following the crisis, individuals became more likely to remain in unstable employment than to leave it. This result does not support Hypothesis 2 as the crisis didn't make individuals previously in unemployment more likely to enter unstable employment compared to the pre-crisis period. However, this does lend some

	(1)	(2)	(3)	(4)	(5)
$y_{(t-1)}$ (ref: Stable)					
Unemployment	3.125***	2.883***	3.113***	3.114***	3.130***
	(0.192)	(0.218)	(0.192)	(0.192)	(0.192)
Unstable	1.271***	1.393***	1.265***	1.261***	1.268***
	(0.139)	(0.166)	(0.139)	(0.139)	(0.138)
Crisis (2009+ vs. 2005–2008)	0.391**	0.422*	0.570***	0.381*	0.331*
	(0.117)	(0.162)	(0.134)	(0.148)	(0.148)
Female	-0.142	-0.129	0.029	-0.140	-0.140
	(0.109)	(0.110)	(0.129)	(0.109)	(0.109)
Age (ref: 30–44)					
under 30	-0.463	-0.465	-0.449	-0.454	-0.449
	(0.265)	(0.269)	(0.265)	(0.278)	(0.266)
45+	0.200	0.210	0.215	0.080	0.197
	(0.267)	(0.273)	(0.268)	(0.301)	(0.266)
Education (ref: Upper sec.)					
Tertiary	-0.520***	-0.525***	-0.526***	-0.524***	-0.635***
	(0.136)	(0.137)	(0.137)	(0.136)	(0.170)
Less than upper sec.	0.784***	0.791***	0.790***	0.785***	0.792***
	(0.126)	(0.128)	(0.127)	(0.127)	(0.147)
$y_{(t-1)}$ (ref: Stable) x Crisis					
Unemployment		0.514			
		(0.297)			
Unstable		-0.375			
		(0.251)			
Female x Crisis			-0.446*		
			(0.189)		
Age (ref: 30–44) x Crisis					
under 30				-0.309	
				(0.296)	
45+				0.144	
				(0.225)	
Education (ref: Upper sec.) x Crisis					
Tertiary					0.286
					(0.239)
Less than upper sec.					-0.022
					(0.207)
N			23,310		
N indiv.			6,424		

Table 7.4 – Results for UK: Unemployment vs. Stable Employment
Robust std. errors in brackets; *** p < 0.001, ** p < 0.01, * p < 0.05
Data Sources: British Household Panel Study, UK Household Longitudinal Study

	(1)	(2)	(3)	(4)	(5)
$y_{(t-1)}$ (ref: Stable)					
Unemployment	1.749***	1.582***	1.738***	1.742***	1.749***
	(0.152)	(0.176)	(0.152)	(0.152)	(0.152)
Unstable	2.406***	2.260***	2.401***	2.398***	2.404***
	(0.085)	(0.092)	(0.084)	(0.085)	(0.085)
Crisis (2009+ vs. 2005–2008)	-0.523***	-0.750***	-0.382***	-0.407***	-0.574***
	(0.069)	(0.097)	(0.098)	(0.087)	(0.082)
Female	0.848***	0.844***	0.917***	0.850***	0.848***
	(0.065)	(0.065)	(0.071)	(0.065)	(0.065)
Age (ref: 30–44)					
under 30	0.073	0.084	0.088	0.161	0.082
	(0.158)	(0.159)	(0.159)	(0.164)	(0.159)
45+	-0.128	-0.128	-0.115	-0.093	-0.128
	(0.127)	(0.129)	(0.128)	(0.138)	(0.127)
Education (ref: Upper sec.)					
Tertiary	-1.002***	-1.003***	-1.005***	-1.004***	-1.065***
	(0.081)	(0.081)	(0.081)	(0.082)	(0.089)
Less then upper sec.	0.534***	0.529***	0.538***	0.538***	0.527***
	(0.079)	(0.079)	(0.079)	(0.079)	(0.086)
$y_{(t-1)}$ (ref: Stable) x Crisis					
Unemployment		0.394			
		(0.276)			
Unstable		0.434*			
		(0.139)			
Female x Crisis			-0.248*		
			(0.110)		
Age (ref: 30–44) x Crisis					
under 30				-0.454*	
				(0.191)	
45+				0.166	
				(0.125)	
Education (ref: Upper sec.) x Crisis					
Tertiary					0.229
					(0.137)
Less than upper sec.					0.031
					(0.136)
N			23,310		
N indiv.			6,424		

Table 7.5 – Results for UK: Unstable vs. Stable Employment
Robust std. errors in brackets; *** p < 0.001, ** p < 0.01, * p < 0.05
Data Sources: British Household Panel Study, UK Household Longitudinal Study

support for Hypothesis 1 as stably employed individuals appear to have been somewhat more likely to remain stably employed relative to individuals who were previously in unstable employment or who were unemployed. Once again, the effects of the other covariates are broadly similar to the model without the additional interaction effect.

Finally, Models three through five include interaction effects between the crisis and the sociodemographic variables. The interaction between the crisis and sex, in the case of unemployment, shows that women became comparatively less likely to enter unemployment. As for age and education, the crisis didn't modify the association between these characteristics and the chances of entering unemployment. In the case of unstable employment compared to stable employment, we also find that the crisis made women less likely to be in unstable employment. This is also the case for the youngest individuals as those aged less than 30 were also less likely to be in unstable employment compared to those aged between 30 and 44.

In Tables 7.B.5 and 7.B.6 we can look at the terms capturing unobserved heterogeneity in more detail. We can see that the initial state is highly correlated with unobserved heterogeneity in the models contrasting unemployment with stable employment, and the models contrasting unstable and stable employment. However, in the case of unemployment vs. stable employment, we find that there is also a correlation between the terms for the crisis and unobserved heterogeneity suggesting that unobserved heterogeneity is in part linked to whether or not we first observed individuals prior to the crisis and the proportion of observations that were after the crisis. We also find a correlation in relation to age and unobserved heterogeneity for this outcome in the case of the within-individual means for those aged 45 and over as well as those who were initially in this age group. This is not the case for unstable vs. stable employment where there is a relatively weak link between age and unobserved heterogeneity. Finally, the covariance between the random effects for the two outcomes is significant and positive suggesting that individuals who are more likely to be unemployed are also more likely to be in unstable employment (Steele 2011, 12).

To conclude, contrary to Switzerland, the results indicate that crisis increased individuals' chances of being unemployed overall. However, the crisis didn't make individuals more or less likely to transition to unemployment in relation to their previous employment situation. This indicates that the increased risk of being unemployed after the crisis didn't only affect the most precarious members of the labour market. It did, however, make individuals in unstable employment more likely to remain in unstable employment relative to stably employed individuals. This results provide partial support for Hypothesis 1 but do not support Hypothesis 2. As for the sociodemographic characteristics, the clearest result is that women, compared to men, were less affected by the crisis in relation to their chances of being in unstable employment or unemployment.

7.6 Conclusion

In this chapter we combined latent class analysis with dynamic panel models in order to model transition processes for latent employment states measured by multiple objective indicators. We estimated a latent class model for all time points where we fixed the item-response probabilities to be equal over time in order to ensure that the interpretation of the latent states wouldn't change over time. From this latent class model, we then estimated for each individual, at each time point, their probability of belonging to each latent class. As latent class assignment is a probabilistic procedure, we also had to take into account that individuals can have non-zero probabilities of belonging to multiple classes. We did this using the "pseudo-class" method where we randomly assigned each individual at each time point using the distribution of their class assignment probabilities 20 times. We then used this assignment as our dependent variable for our dynamic multinomial logit panel model which we estimated 20 times. We then pooled the estimates using Rubin's (1987) rules as in the case of multiple imputation.

We applied this combination of methods to the case of employment transitions between unemployment, precarious employment, and secure employment in the aftermath of the 2008 Financial Crisis in the UK and Switzerland. Based on different definitions of job quality and labour market precarity, precarious employment was defined using a classification derived from the latent class analysis and four objective indicators – employment status, contract type, working hours, and wages – of individuals' employment situation.

The results of the latent class analysis show that in the UK the main opposition in terms stable and unstable employment is related to individuals' wages. The unstable employment class is characterized by a much higher probability of having low wages, as well as higher probability of working part-time. In Switzerland, the main distinction is also related to wages as the unstable employment class is also characterized by a higher probability of having lower wages, though the difference relative to the stable employment class is not as marked as in the case of the UK. Additionally, individuals in unstable employment class are more likely to have fixed-term contracts as well as part-time employment. Comparing the two countries, the main distinction is that contract type plays a more important role in distinguishing between more precarious and less precarious employment in Switzerland than in the UK. This is somewhat in line with the descriptive data presented in Section 7.3 which shows that both part-time work and fixed-duration contracts are less common in the UK.

The results of the dynamic panel models show that in Switzerland, the crisis had no clear effect on employment transitions. While the crisis did make it more likely for individuals to be unemployed overall, this is not the case for precarious employment. In fact, the trend is towards a *decrease* in the chances of individuals being in unstable employment following the crisis. However, this is once any state dependence, or the tendency for individuals to remain in the same employment position, is taken into account. When looking at the interaction terms between the crisis and individuals' previous employment status, there seems to be no evidence in Switzerland that the crisis made individuals in less secure forms of employment or unemployment more likely to transition to unemployment or precarious employment compared to those in secure employment. However, in the case of the UK there is evidence indicating that the crisis made individuals previously in unstable employment more likely to remain in unstable employment.

Coming back to our hypotheses, in the case of Switzerland our results do not support our hypotheses. We find that the crisis didn't make individuals more or less likely to transition to unemployment or unstable employment in relation to their previous employment situation. In other words, the crisis had no effect on the relationship between individuals previous labour market status and their subsequent labour market status. Thus in Switzerland, there is no indication of a decline in job quality in relation to previous employment. In the UK we do find some evidence supporting Hypothesis 1 as relative to individuals previously in stable employment, the crisis made those who were previously in unstable employment more likely to remain there. There is, however, no evidence that individuals became more likely to move to unstable employment from unemployment after the crisis and thus no support for Hypothesis 2. Moreover, in both countries, the crisis seems to have reduced the likelihood of being in unstable employment overall. Overall, these results are in line with the results from Leschke et al. (2012) which showed that job quality didn't really decline in Europe after the crisis and supports Gallie and Ying (2013) results showing that job quality didn't decrease outside Southern and Eastern Europe. Nevertheless, there is some evidence in the UK of a potential increase in polarization in job quality as individuals in unstable employment became more likely to remain unstable employed after the 2008 Financial Crisis.

As for sociodemographic characteristics, in Switzerland the main difference is related to sex with women being more likely to be unemployment or in unstable employment than men. This is in line with the literature on precarious employment which finds that women are more often employed have less secure jobs than men (Kalleberg 2000; Kalleberg et al. 2000; Vosko et al. 2009). We found no differences in relation the highest level of education achieved nor age in the case of unemployment vs. stable employment. However, there are educational differences in the chances of being in unstable employment as found in previous work (Kalleberg et al. 2000; Müller 2005; Kalleberg 2012; Kretsos and Livanos 2016; Pyöriä and Ojala 2016). Compared to an upper secondary level of education, having less than upper secondary level of education increases the chances of being in unstable employment while a tertiary level of education reduces them. In the UK, there were no differences of note in relation to age either. However, there were substantial differences relating to education both for unemployment and unstable employment. Compared to an upper secondary level of education, individuals with a tertiary level were less likely to be unemployed but also be in unstable employment while the opposite situation was true for a tertiary level of education.

In the case of Switzerland, the interactions between the crisis and sociodemographic characteristics show that the youngest individuals became less likely to be in unstable employment or unemployment after the crisis. We also find that individuals with a tertiary level of education became more likely to be in unstable forms of employment following the crisis. In the UK, we mainly find that crisis made women less likely to be in unemployment, which is in line with macro-level results (Keeley and Love 2010), or unstable employment. Additionally, individuals under 30 became less likely to be in unstable employment after the crisis but this is not the case for unemployment.

Our approach of combining LCA with dynamic multinomial logit panel models using Rabe-Hesketh and Skrondal's (2013) improved version of Wooldridge's (2005) solution to the initial conditions problem allowed us to model individual transitions between unemployment, precarious employment, and stable employment over time in the aftermath of the crisis. The advantage of taking this approach to modelling transitions in this application is that it allows us to incorporate a mutli-dimensional operationalization of our dependent variable and model transitions between more than two states which is not possible in standard dynamic panel models for categorical data. This method also better allows us to take into account the effects of unobserved heterogeneity on transitions, and reduce bias related to the initial conditions problem, i.e. bias related to the fact that we don't observe individual processes from the very beginning, compared to methods such as LTA which take a naive approach to estimating the transition model. Moreover, as LTA models are most often estimated in multivariate frameworks, our approach also allows us to incorporate observation-level variables that vary within individuals but not between individuals.

There are, however, limitations that must be taken into account. One of the main limitations is the operationalization of vulnerable employment. This is in part due to changes in data collection over time, and the difficulty in employing comparable indicators between the SHP, the BHPS, and the UKHLS. Crucial indicators such as desired work hours are not consistently available in the UKHLS, and in the transition from the BHPS to the UKHLS, many more detailed indicators of job quality – such as control, autonomy, or subjective employment security – disappeared or the manner in which the question is asked changed. Nevertheless, the chosen indicators describe individuals' objective employer–employee relationship fairly well and are indicators that are measured consistently between all three surveys with similar questions and responses.

Another limitation is the nature of panel data and attrition with individuals in difficult situations being more likely to drop out (Behr et al. 2005) meaning that we generally end up with the most stable individuals. As such, we may actually be underestimating the probability of individuals transitioning from less to more precarious forms of employment or unemployment. Thus the limitation affects our application, but also our method as it doesn't deal explicitly with attrition.

There are also further avenues for investigation and improvements in our method. Firstly, using a "3-step" approach where class assignments are taken from an LCA model and then subsequently reused for analysis often leads to an underestimation of the effects of covariates when compared to a single-step estimation. Most proposed correction methods are usually meant for cross-sectional analyses. However, while there are methods for longitudinal cases (Asparouhov and Muthén 2014; Mari et al. 2016) which outperform the "pseudo-class" method we applied, they are mainly implemented in software for multivariate longitudinal analysis which would have prevented us from estimating the effect of observation-level variables (pre-crisis vs. crisis).

Another possible improvement relates to our dynamic panel model only corresponding to a first order Markov chain i.e. we only lag the dependent variable by one time period. To better test for the possibility of individuals being more likely to enter less secure forms of employment indirectly in relation the crisis, a second-order chain (that is lagging the dependent variable twice) would be necessary. However, this would make the model estimation more difficult, and would further reduce the available data as we would be required to have at least three consecutive observations per individual.

Nevertheless, this chapter offers an interesting insight into employment transitions in the aftermath of the crisis by combining latent class analysis with dynamic longitudinal panel models for categorical data. It illustrates a method which allows for combining latent class models with more complex specifications for the transition model. Moreover, it illustrates the trade-offs in employing latent classes in a longitudinal perspective. More complex transition models estimated separately from the latent class model allow taking somewhat correcting for biases related to now observing processes from the beginning at the cost of introducing a (downward) bias in the relationship between latent classes and covariates while standard latent transition models don't take into account heterogeneity or initial conditions. Nevertheless, further developments could include multilevel latent transition models that jointly estimate the latent classes and the transitions, and investigating other techniques for bias correction in longitudinal 3-step approaches that would allow the inclusion observation-level covariates.

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7.A Latent Class Prevalences

7.A.1 Switzerland

	Unemployment	Unstable	Stable
2005	0.029	0.404	0.568
2006	0.031	0.376	0.593
2007	0.019	0.330	0.651
2008	0.016	0.315	0.669
2009	0.022	0.325	0.652
2010	0.021	0.284	0.695
2011	0.020	0.272	0.708
2012	0.014	0.254	0.733

Table 7.A.1 – Latent Class Prevalences for Switzerland
Data Source: Swiss Household Panel

7.A.2 UK

	Unemployment	Unstable	Stable
2005	0.067	0.326	0.607
2006	0.057	0.296	0.646
2007	0.051	0.267	0.682
2008	0.059	0.232	0.709
2010	0.061	0.187	0.751
2011	0.056	0.181	0.763
2012	0.063	0.167	0.770

Table 7.A.2 – Latent Class Prevalences for the UK
Data Sources: British Household Panel Study, UK Longitudinal Household Study

7.B Unobserved Heterogeneity Parameters

7.B.1 Switzerland

	(1)	(2)	(3)	(4)	(5)
Age mean					
under 30	0.251	0.287	0.246	0.576	0.209
	(0.892)	(0.913)	(0.900)	(0.867)	(0.897)
45+	0.239	0.235	0.246	0.395	0.210
	(0.558)	(0.558)	(0.560)	(0.578)	(0.560)
Crisis Mean	-1.117*	-1.124*	-1.124*	-0.988	-1.093*
	(0.521)	(0.531)	(0.524)	(0.527)	(0.524)
Age$_0$					
Under 30	-0.042	-0.057	-0.045	-0.268	-0.036
	(0.486)	(0.493)	(0.488)	(0.490)	(0.488)
45+	0.224	0.215	0.221	0.146	0.232
	(0.319)	(0.324)	(0.320)	(0.322)	(0.320)
Crisis$_0$	0.006	0.009	0.039	-0.026	-0.015
	(0.782)	(0.784)	(0.782)	(0.803)	(0.783)
y_0					
Unemployment	2.142***	2.100***	2.155***	2.199***	2.164***
	(0.340)	(0.351)	(0.341)	(0.345)	(0.339)
Unstable	-0.028	-0.054	-0.023	-0.023	-0.028
	(0.182)	(0.186)	(0.182)	(0.183)	(0.182)
Intercept	-4.908***	-5.077***	-5.056***	-5.169***	-4.954***
	(0.343)	(0.366)	(0.351)	(0.375)	(0.351)
σ_1^2	2.345	2.511	2.358	2.419	2.370
	(0.557)	(0.567)	(0.559)	(0.574)	(0.563)
σ_{12}^2	0.422*	0.431*	0.424*	0.432*	0.423*
	(0.142)	(0.144)	(0.142)	(0.143)	(0.143)

Table 7.B.3 – Unobserved heterogeneity parameters unemployment vs. stable employment Switzerland
Data Source: Swiss Household Panel

	(1)	(2)	(3)	(4)	(5)
Age mean					
under 30	0.401	0.401	0.402	0.531*	0.397
	(0.248)	(0.248)	(0.248)	(0.255)	(0.249)
45+	0.297*	0.298*	0.297*	0.319*	0.305*
	(0.140)	(0.140)	(0.140)	(0.141)	(0.140)
Crisis mean	0.130	0.130	0.129	0.180	0.155
	(0.161)	(0.161)	(0.161)	(0.164)	(0.162)
Age_0					
under 30	-0.092	-0.092	-0.092	-0.155	-0.094
	(0.146)	(0.146)	(0.146)	(0.149)	(0.146)
45+	-0.107	-0.107	-0.107	-0.111	-0.107
	(0.087)	(0.087)	(0.087)	(0.088)	(0.087)
Crisis_0	0.135	0.135	0.135	0.120	0.136
	(0.216)	(0.216)	(0.216)	(0.216)	(0.215)
y_0					
Unemployment	0.576***	0.580***	0.577***	0.586***	0.580***
	(0.164)	(0.166)	(0.164)	(0.164)	(0.164)
Unstable	0.384***	0.382***	0.385***	0.386***	0.385***
	(0.051)	(0.052)	(0.051)	(0.052)	(0.051)
Intercept	-1.464***	-1.471***	-1.463***	-1.507***	-1.445***
	(0.088)	(0.089)	(0.091)	(0.091)	(0.089)
σ_2^2	0.434	0.438	0.434	0.437	0.436
	(0.055)	(0.055)	(0.055)	(0.055)	(0.055)
σ_{12}^2	0.422*	0.431*	0.424*	0.432*	0.423*
	(0.142)	(0.144)	(0.142)	(0.143)	(0.143)

Table 7.B.4 – Unobserved heterogeneity parameters unstable vs. stable employment Switzerland
Data Source: Swiss Household Panel

7.B.2 UK

	(1)	(2)	(3)	(4)	(5)
Age mean					
under 30	0.321	0.303	0.312	0.414	0.308
	(0.460)	(0.464)	(0.460)	(0.462)	(0.460)
45+	-0.945*	-0.945*	-0.966*	-0.916*	-0.935*
	(0.420)	(0.426)	(0.420)	(0.417)	(0.418)
Crisis mean	-1.067**	-1.068**	-1.027*	-1.045**	-1.062**
	(0.326)	(0.326)	(0.326)	(0.327)	(0.326)
Age$_0$ (ref: 35-44)					
under 30	0.324	0.338	0.319	0.288	0.326
	(0.271)	(0.273)	(0.271)	(0.273)	(0.271)
45+	0.808*	0.788*	0.807*	0.834*	0.801*
	(0.270)	(0.272)	(0.270)	(0.278)	(0.270)
Crisis$_0$	1.002*	0.866	1.037*	0.994*	0.989*
	(0.434)	(0.472)	(0.434)	(0.432)	(0.433)
y_0					
Unemployment	2.895***	3.037***	2.920***	2.916***	2.896***
	(0.273)	(0.273)	(0.275)	(0.275)	(0.273)
Unstable	1.124***	1.117***	1.143***	1.137***	1.131***
	(0.164)	(0.166)	(0.165)	(0.164)	(0.164)
Intercept	-4.765***	-4.814***	-4.856***	-4.775***	-4.746***
	(0.193)	(0.202)	(0.199)	(0.196)	(0.194)
σ_1^2	1.833	1.915	1.866	1.851	1.832
	(0.357)	(0.359)	(0.360)	(0.359)	(0.358)
σ_{12}^2	0.977***	1.010***	1.008***	0.992***	0.986***
	(0.203)	(0.201)	(0.205)	(0.204)	(0.203)

Table 7.B.5 – Unobserved heterogeneity parameters unemployment vs. stable employment UK
Data Sources: British Household Panel Study, UK Household Longitudinal Study

	(1)	(2)	(3)	(4)	(5)
Age mean					
under 30	0.368	0.374	0.353	0.424	0.359
	(0.273)	(0.273)	(0.274)	(0.277)	(0.274)
45+	0.156	0.161	0.141	0.187	0.160
	(0.213)	(0.212)	(0.213)	(0.214)	(0.213)
Crisis mean	-0.134	-0.151	-0.126	-0.116	-0.138
	(0.185)	(0.184)	(0.186)	(0.186)	(0.185)
Age$_0$					
under 30	-0.279	-0.288	-0.279	-0.341	-0.278
	(0.173)	(0.173)	(0.174)	(0.176)	(0.173)
45+	-0.057	-0.060	-0.056	-0.082	-0.059
	(0.152)	(0.152)	(0.153)	(0.154)	(0.153)
Crisis$_0$	0.696*	0.723*	0.711*	0.696*	0.678*
	(0.272)	(0.285)	(0.272)	(0.272)	(0.272)
y_0					
Unemployment	1.787***	1.847***	1.805***	1.806***	1.793***
	(0.190)	(0.192)	(0.190)	(0.191)	(0.190)
Unstable	2.052***	2.109***	2.064***	2.063***	2.056***
	(0.112)	(0.113)	(0.112)	(0.112)	(0.112)
Intercept	-3.580***	-3.519***	-3.624***	-3.619***	-3.568***
	(0.103)	(0.104)	(0.105)	(0.105)	(0.103)
σ_2^2	1.400	1.393	1.416	1.415	1.405
	(0.158)	(0.158)	(0.159)	(0.159)	(0.158)
σ_{12}^2	0.977***	1.010***	1.008***	0.992***	0.986***
	(0.203)	(0.201)	(0.205)	(0.204)	(0.203)

Table 7.B.6 – Unobserved heterogeneity parameters unstable vs. stable employment UK
Data Sources: British Household Panel Study, UK Household Longitudinal Study

Chapter 8 Conclusion

The 2008 Financial Crisis, Vulnerability, and Labour Market Outcomes

In this thesis, methods for the modelling of vulnerability in a dynamic perspective were proposed and illustrated with two applications concerning labour market outcomes following the 2008 Financial Crisis. One of the main macro-level observations regarding labour market outcomes in the aftermath of the 2008 Financial Crisis is the relative difference in vulnerability between men and women in relation to unemployment. In general, the crisis disproportionately affected men – it has sometimes been referred to as a “mancession” (Bargain and Martinoty 2019) – unlike previous economic downturns (Keeley and Love 2010; Pissarides 2013; Tridico 2013). In the first application in Chapter 6, the results from the latent growth curve analysis show that in the UK, women were overall less likely to enter unemployment from 2008 onward. However, this was not the case in Switzerland showing the importance of taking into account context in the case of labour market outcomes during the Great Recession. Countries whose economies were less affected by the downturn didn’t see as much of difference between men and women in their likelihood of experiencing unemployment. It is also interesting to note that in the case of the UK, the results don’t show the gap narrowing over time. This would suggest that the crisis potentially made male workers more likely to be unemployed and that this remains the case even after the economy recovered.

Age-related differences in vulnerability weren’t substantial in either the UK or Switzerland. While younger individuals were generally more likely to experience unemployment, this is generally the case even when the economy isn’t in recession. Moreover, the results show that over time, the youngest individuals at the time of the crisis didn’t become more vulnerable in either the UK or Switzerland as their chances of becoming unemployed didn’t increase over time. In fact, in the UK, there is even some evidence that the youngest employed individuals potentially became less vulnerable after the crisis. This was to be expected and broadly in line with macro-level evidence showing that the large increase in youth unemployment related to the crisis in Europe was mainly concentrated in Southern European countries such as Spain, Portugal, Greece, or Italy rather than Northern or Central Europe (Choudhry et al. 2012; O’Higgins 2012; Tåhlin 2013). This once again shows the importance of context as it can be argued that the UK’s economy was exposed earlier to the consequences of collapse of the US housing market than many other European countries (Laeven and Valencia 2010).

Taking individual resources, in Switzerland it would seem that individuals’ highest level of education plays no role in explaining differences in the chances of experiencing unemployment. This is not entirely unexpected as Switzerland has a dual-education system like most coordinated market economies (Hall and Soskice 2001; Hall and Gingerich 2009) which tends to reduce differences in unemployment related to educational achievement. In the UK, however, there is a more stark contrast between individuals with different levels of education in relation to their odds of becoming unemployed. The UK being a liberal market economy (Hall and Soskice 2001; Hall and Gingerich 2009), like the US, means that educational achievement is a more important asset and plays a larger role in individual vulnerability. Not only were individuals with lower levels of education more likely to experience unemployment, they also became increasingly vulnerable over time suggesting that they had more difficulty coping than individuals with higher levels of education in the UK. The most highly educated, on the other hand, are overall less likely to experience unemployment, but there's no change over time relative to individuals with intermediate levels of education.

Focusing on the results from the combined latent class and dynamic panel model analysis concerning unstable employment in Chapter 7, we find that the crisis didn't make individuals more likely to have unstable employment. In fact, individuals in stable employment became less likely to enter unstable work following the crisis in both the UK and Switzerland. In both countries, we found no specific age-related differences in the chances of being in unstable employment in general which somewhat goes against evidence showing that younger individuals are generally more likely to be in unstable employment (Choudhry et al. 2012). Moreover, younger individuals, relative to older workers, became less vulnerable over time in both the UK and Switzerland as they became less likely to be in unstable employment despite not being significantly more vulnerable otherwise.

As for gender differences, in both Switzerland and the UK, women are more vulnerable overall due to their increased likelihood of having unstable jobs. However, relative to men, women saw a reduction in their vulnerability with the crisis in the UK by becoming less likely to be unemployed than men. Education also plays a role with higher levels of education being associated with lower chances of being in unstable forms of employment in both the UK and Switzerland. Interestingly, in Switzerland the crisis led to individuals with tertiary levels of education becoming slightly more vulnerable as their chances of being in unstable employment increased. This is not the case in the UK, as education had no effect on post-crisis vulnerability.

As for individuals' previous labour market status, it played a preponderant role in explaining individuals' likelihood of being in unstable employment as once individuals have entered unstable employment, they are extremely likely to remain there. This may potentially explain why there is no observed relationship with individuals' age as younger people are more likely to enter the labour market through unstable positions. Moreover, in the UK the crisis further accentuated this relationship by making individuals in unstable employment even more likely to remain in such forms of work. These results therefore suggest that individuals who were already more vulnerable due to their greater chances of having unstable employment remained so during the crisis. Those that initially weren't vulnerable, didn't become more so over time which supports assessments by Leschke et al. (2012) and Gallie and Ying (2013).

What these results also show is the importance of taking into account context even when individuals are exposed to the same, or similar, sources of stress at similar points in time. The most notable difference between the UK and Switzerland the importance of education in relation to the chances of being unemployed. Taking into account context in the analysis of the consequences of the 2008 Financial

Crisis, especially in the case of Europe, is essential as the consequences of the crisis varied substantially between countries especially in relation to labour market outcomes (Tåhlin 2013; Tridico 2013).

Methods for Modelling Vulnerability

Moving beyond the substantive results of the applications in Chapters 6 and 7, let's return to the choice of methods and the implications for the modelling of vulnerability in both applications. The analysis of vulnerability in Chapter 6 used latent growth curve models. As we saw in Section 4.1, growth curve models are method that can potentially be used to model trajectories of vulnerability over time after being exposed to sources of stress. Latent growth curve models are a very flexible and general method for investigating change over time and can be used in a wide variety of domains. While initially developed as a method to model change over time for continuous dependent variables, as we saw in Sections 4.1.1 and 4.1.4 more recent developments also allow for modelling change over time for categorical dependent variables. Thus latent growth curve models allowed us to get an overall picture of how individual vulnerability, conceived as the chances of being unemployed, evolved over time during the recession.

It also allowed us to understand *how* trajectories were influenced by differences in individual characteristics and resources. Moreover, these models, under certain assumptions, can take into account differences between individuals that are not directly observed by allowing the variables describing trajectories to vary between individuals. The results from growth curve models are not very difficult to interpret and allow for understanding potentially very long-term trends in an intuitive manner.

Nevertheless, growth curve models are more of a descriptive, albeit holistic, approach to understanding vulnerability processes. One particular issue is that these models require that the form of change over time be defined by the researcher. In the case of the application in Chapter 6, a linear time specification was chosen. However, estimating potentially complex trajectories such as those illustrated in Figure 3.1 is possible, but more difficult, with such an approach. However, modelling complex trajectories also requires that there be enough change over time to be able to model these trajectories. The problem in our case in the analysis of unemployment is that there is relatively little change over time as evidenced by Appendix 6.A. Moreover, because of the annual nature of the data, we don't necessarily observe every individual's movements between employment and unemployment, and thus all of their positions along their vulnerability trajectory.

Another potential downside of latent growth curve models is that they aren't a tool specifically suited to investigating absolute vulnerability. Because growth curve models are designed to compare change over time between individuals, this means that the study in Chapter 6 is an analysis of the *relative* vulnerability of individuals in relation to their chances of unemployment following the 2008 Financial Crisis. Consequently we know which individuals were more likely than others to experience a greater likelihood of experiencing unemployment. Moreover, in the case of binary dependent variable, such as employment vs. unemployment, what is being modelled by a growth curve model is an underlying latent linear variable which measures individuals' likelihood of being unemployed. In such a case, it is difficult to establish an absolute threshold on the scale of this latent variable past which individuals will experience negative consequences. Nevertheless, the definition of thresholds is a general issue in the analysis of vulnerability especially in the case of economic vulnerability or poverty (Nolan and Whelan 2010; Lucchini and Assi 2013).

In contrast to the more descriptive and holistic approach taken in the analysis of trajectories in Chapter 6, the combination of latent class analysis and dynamic panel models in Chapter 7 focuses more on *transitions*. If we compare this to Figure 3.1 in Section 3.3, transition models can be thought of as modelling movements between different positions associated with different levels of negative consequences or undesirable outcomes. Transitions models can be used to model movements between different parts of the vulnerability process in a longer-term perspective. Or, as is the case of the approach taken in Chapter 7, they can be used to investigate short-term change brought about by a stressor – in this case the 2008 Financial Crisis. The aim was to understand what the 2008 Financial Crisis did for individuals' job security relative to the situation prior to the crisis. Consequently transition models, such as the dynamic panel model, serve to analyse what makes individuals more likely to move from one state to another. The principal focus of transition models is to understand which factors can describe differences in individuals' chances moving between different categories of negative consequences after being faced with a source of stress.

The role of resources and individual characteristics was also somewhat different in the case of transition models. Rather than allowing us to understand the effects of these elements on the overall trajectory, transition models focus on how resources can influence the chances of transitioning to a status corresponding to a higher or lower level of negative consequences. As was done in the application in Chapter 7, transition models can be used to investigate the different effects of exposure to a stressor. Transition models can also typically be used to take into account relationships between individuals' present states in relation to their past state(s). This allows for understanding transitions as being part of a larger process where the past continues to influence the present.

An additional difference is that this approach also employed a multidimensional measure of individuals' labour market position. This better allowed for investigating the more complex question of job quality, and individuals' employment situations, by going beyond just a simple dichotomy. While it is also possible to model multi-dimensional concepts using latent growth curve models, they are not particularly well suited to this when using multiple categorical indicators.

However, there are some disadvantages to using transition models. The first is that they are harder to interpret relative to other longitudinal latent variable models such as latent growth curve models. The second disadvantage is that they are potentially difficult to estimate especially with many time points and many variables being grouped together into different latent classes. This is partially one of the reasons why the application in Chapter 7 used a multi-step approach to estimate the model with the latent class component estimated separately from the transition model. A side effect is that this can potentially underestimate the effect of resources or other individual characteristics on the chances of transitioning between states.

Another potential disadvantage of transition models is the fact that they are not a holistic method. It is possible to extend transition models so as to allow the chances of transiting between statuses to vary over time as shown in Section 4.2.3. This can be thought of as being between a transition- or event-based approach and a holistic one as it allows the chances of transitioning to vary over time. It is also possible to use latent class models to estimate groups, or clusters, of whole trajectories in a manner similar to sequence analysis (Barban and Billari 2012; Piccarreta and Studer 2018) as an alternative to using latent growth curve models with categorical outcomes. However, unlike latent growth curve models, time is not explicitly included and thus it classifies individuals into certain types of trajectories rather than explicitly modelling how those trajectories vary over time.

Directions for Further Research

One of the specificities of the applications presented in this thesis is the stressor: the 2008 Financial Crisis. The crisis was of a systemic nature and affected entire countries and societies. Thus, it is a stressor to which it is likely *all* individuals were exposed to regardless of their socioeconomic positions. However, not all sources of stress, as noted by Pearlin (1989), can be considered to be exogenous or independent from individuals' personal situations. In the social sciences, sources of stress are typically associated with socioeconomic characteristics. Sources of stress such as divorce or unemployment do not have the same chances of affecting all individuals. As such, taking into account the fact that individuals have different likelihoods of experiencing a stressor, what is referred to as differential exposure (Aneshensel 1992), could be important in understanding differences in vulnerability. One approach to modelling this potential non-independence between observing vulnerability and exposure to sources of stress are selection models (Heckman 1976, 1979; Winship and Mare 1992). Selection models can potentially be combined with growth curve models or other latent models such as latent class analysis (Rabe-Hesketh et al. 2004; Enders 2011) to account for differences in vulnerability between individuals in relation to differences in the chances of exposure to a source of stress.

A second avenue to explore in relation to stressors is modelling processes of vulnerability when the stressor is recurring or a chronic strain. This could potentially be integrated as a time-varying covariate in growth curve models and transition models such as dynamic panel models or latent transition analysis. However, it would be more complicated to integrate such types of stressors in more holistic approaches to analysing categorical outcomes such as longitudinal latent class analysis. A third possible extension would be the investigation of the consequences of exposure to multiple stressors at once. However, doing so can potentially be very complicated especially if the stressors don't necessarily occur at the same point in time. It is much less clear how this could be investigated with the latent variable models presented in this thesis.

Another consideration is the manner in which the outcome is modelled in the study of vulnerability. In this thesis, the outcome was limited to one specific domain: the labour market. While the second application in Chapter 7 used a multidimensional measure of the outcome, it nevertheless only focused on a single outcome. Pearlin

(1989) in particular argues that vulnerability should not necessarily be analysed in relation to a single domain or outcome. Latent variable models offer multiple manners to model multiple outcomes simultaneously. One option is to use a curve-of-factors model as discussed in Section 4.1.5 and model the evolution of a combined outcome composed of multiple indicators over time. The same can be done in the case of latent class models where indicators for different outcomes are combined together. However, this isn't necessarily an ideal solution as these models were typically designed for modelling multiple indicators of a *single* underlying complex concept in a specific domain.

Another potential solution for continuous outcomes is the use of bivariate growth curve models or dual change-score models as described in Section 4.1.5. These models which involve the simultaneous estimation of multiple growth curves can be used to jointly model reciprocal effects of different processes of vulnerability over time. Thus in such models it would be possible to link change over time in, for instance, physical health and economic well-being after exposure to a source of stress. Such models also potentially allow for testing temporal precedence of processes to investigate whether changes in vulnerability in one domain subsequently lead to changes in another or vice versa. However, these models can be potentially difficult to estimate (Grimm, Ram, and Estabrook 2017, 429).

There is also the question of measuring and incorporating resources. In the applications in Chapters 6 and 7, one main resource is considered: education. While individuals' education attainment is potentially among the most important social resources available (Becker 1994; Pallas 2003; Frytak et al. 2003; Mirowsky and Ross 2003), the interplay between different types of resources and the multidimensionality of resources is also an avenue for further investigation.

Concerning the first point, better understanding how resources mutually influence each other, can be potentially investigated in the short-term with a sequential design mediation model (Kraemer et al. 2001; Kraemer et al. 2008). This mediation design can be used to assess the mediating influence of a resource measured a time t on the relationship between a resource measured at $t-1$ and an outcome at $t+1$. Such interplay can be estimated with the models and techniques described in Chapter 5 and is an extension of standard cross-sectional mediation models. This type of model has been criticized (Maxwell et al. 2011; Mitchell and Maxwell 2013) and alternatives based on parallel process models such as multivariate growth curve models or latent dual-change score models have been proposed for more intensive longitudinal data (Selig and Preacher 2009; Maxwell et al. 2011; Mitchell and Maxwell 2013). While more complex, these approaches also have the potential for analysing dynamics of resource accumulation over time as resources are not necessarily static and can change not just before exposure to a source of stress but also after.

As for the second point, the multidimensionality of resources, there are examples such as the multiple deprivation measures used in studies on poverty and social exclusion as briefly discussed in Section 3.3. Being designed for the analysis of multidimensional concepts measured with multiple indicators, latent variable models can incorporate such methods for measuring resources and the underlying latent variable measuring resources can be continuous or categorical. In a longitudinal perspective, using latent variables to measure resources can introduce some additional difficulties relating to the reliability of measuring the same concept at different time points. This can require additional validation, as in the case of curve-of-factor models, such as testing factorial or measurement invariance (Meredith 1993) to ensure that a resource is being measured the same way over time and that it can be interpreted in the same manner.

To conclude, there are many possibilities to further expand and improve the measurement and modelling of vulnerability to better understand the outcomes people face when exposed to sources of stress. Nevertheless, there are trade-offs to be made between creating a complete, but potentially very complex, statistical model to investigate vulnerability processes. In certain cases the interest may only be in short-term dynamics such as the occurrence of negative outcomes, while in others a longer-term, but potentially more descriptive, view may be more suitable. The analysis of vulnerability is potentially very broad, and the framework and methods presented here can potentially be applied to a number of sources of stress and many different outcomes. There are nevertheless still many aspects of modelling vulnerability to explore and this will continue to be the case as latent variable models are further developed.

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