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The Great Recession and Trajectories of Vulnerability to Unemployment in the UK and Switzerland

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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, Rani, and Sekerler Richiardi 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 paper, vulnerability to unemployment is conceptualised as an individual's *latent* risk of experiencing unemployment at a given point in time. The aim of the paper 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 both within- *and* 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 generalised 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 paper we take a holistic approach to studying vulnerability to unemployment over time by using growth curve models. Instead of decomposing trajectories into discrete transitions and risk losing the sight of the larger picture (Piccarreta and Studer 2018), growth curve models allows 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 2016, 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 paper is organised as follows: first the Great Recession and its consequences for the labour market, particularly in the case of the UK and Switzerland, is considered. Second, the concept of vulnerability is presented along with an operationalization 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.

2 The Great Recession and the Labour Market

The Great Recession finds its roots in the collapse of the subprime mortgage market in the United States and the ensuing financial crisis. With the number of defaults increasing as housing prices dropped in the US, banks announced major losses. While there were already signs of a potential crisis related to sub-prime mortgages in 2007 and early 2008, it is a cascade of events in the fall of 2008 – the Lehmann Brothers' bankruptcy, the government take-over of Fannie Mae and Freddie Mac (Chodorow-Reich 2014, 17–19; Fligstein and Habinek 2014, 650–651) – that are considered to be the cause. 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 fact, it is only in 2017 that unemployment rates in Western countries have begun to return to pre-crisis levels OECD (2018, 11).

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 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 – 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 (Hall and Soskice 2001; Hall and Gingerich 2009), Switzerland's labour market has more in common with liberal countries as its employment regulation are more flexible especially when it comes to the ability of employers to dismiss workers (Emmenegger 2010). While Switzerland did see a decline in its GDP and an increase in unemployment, it wasn't nearly as marked as it was in the rest of Europe (Baur, Bruchez, and Schlaffer 2013).

In addition to differences between countries, not all workers were as likely to be negatively affected by the crisis. Women were actually less affected according to OECD data. 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, Tåhlin (2013) finds that unemployment among women didn't increase as sharply after the crisis (see also Figure 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 2), however the increase was more pronounced for men with gap between unemployment rates for the two sexes narrowing over time.

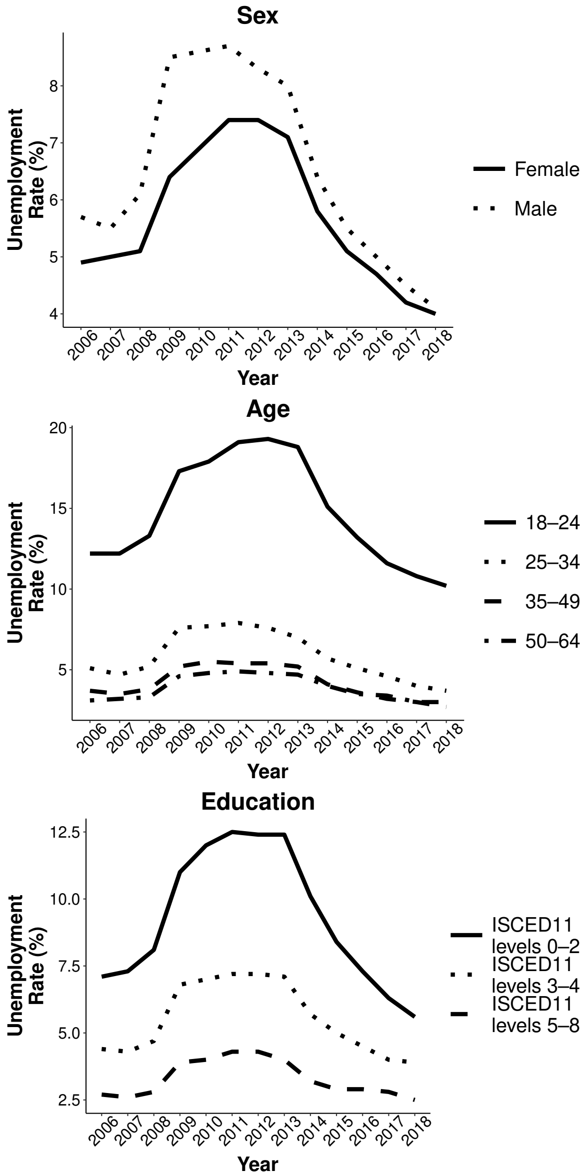

Figure 1: Unemployment Rates for UK; Sources: Eurostat and UK LFS

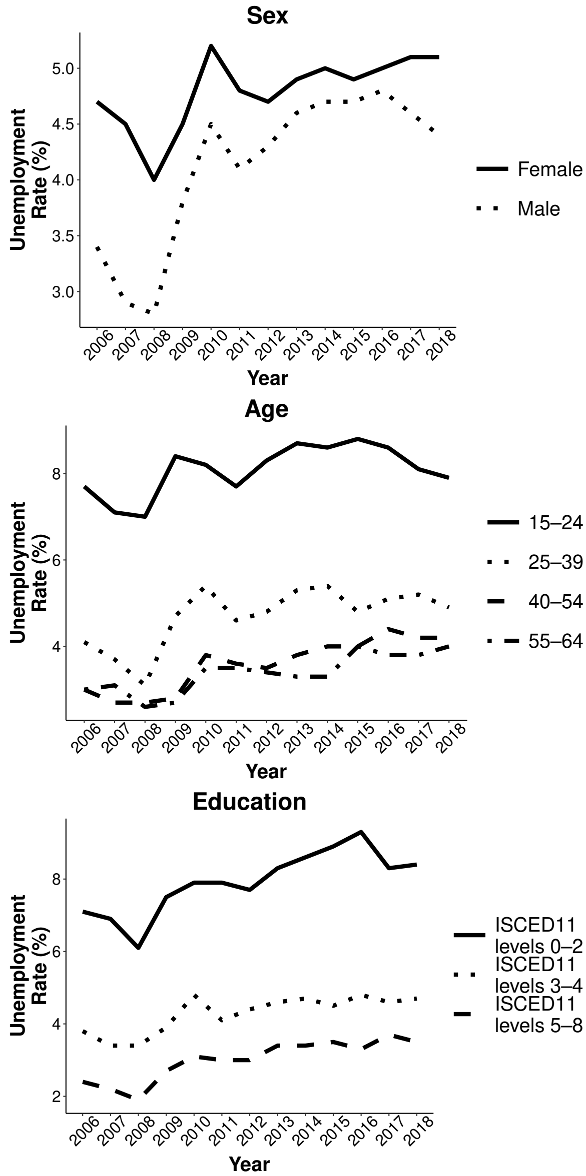

Figure 2: Unemployment Rates for Switzerland; Source: Swiss Federal Statistics Office

The crisis also disproportionately affected younger workers. Looking at more recent data for the UK (Figure 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 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 vulnerable 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 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 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 above analyses 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 paper 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.

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* to unemployment in a period covering 8 years after the crisis occurred. In this section we briefly overview two main conceptions of vulnerability, a "dynamic" view and a "static" view, and how they can shed light on individual vulnerability to unemployment following the Great Recession.

In the social sciences work on vulnerability, and the closely related notion of precariousness, mostly focuses on individuals in a position of uncertainty who are at risk of entering a less desirable situation such as poverty or social exclusion. Generally vulnerability is thought of as a state where individuals lack the resources to prevent or protect themselves from "damage" – i.e. a deterioration of their situation – when exposed to an adverse event or "stressor" (Chambers 1989, Castel 1995, Paugam 2007, Ranci 2010; see also Blaikie et al. 1994; Luers et al. 2003; Turner II et al. 2003; O'Brien et al. 2004 for similar definitions in the environmental sciences).

Compared to this somewhat static view, a more dynamic approach to vulnerability can be adopted. 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), Spini et al. (2013, 19) and Spini, Bernardi, and Oris (2017, 8) consider vulnerability as *process* with three stages: *risk*, *coping*, and *recovery*. For someone to be vulnerable, they actually need to be at *risk* of experiencing a stressor that can potentially lead to negative consequences (this essentially corresponds to the "static" view). The inability to *cope* effectively means that individuals are unable to prevent negative outcomes from occurring once exposed to sources of stress. Finally, *recovery* refers to individuals' ability to overcome the negative consequences brought about by the stressor and return to their pre-stressor situation.

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.

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 hypothesise that:

Hypothesis 1a Initially, males were more vulnerable to 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 to unemployment relative to older individuals (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 to unemployment over time as the economy recovered and labour demand rose.

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

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.

4 Methods & Data

This paper 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.

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).

By contrast, the goal of traditional panel regression models is to measure causality by using longitudinal data to control for individual heterogeneity i.e. the effect of a change in a variable net of the differences between individuals (Andreß, Golsch, and Schmidt 2013, 2–7). They can also be used to check for temporal precedence as longitudinal data can be employed to give the effect on the outcome variable given the value of a variable at a previous time or analyse the effect of a change in the independent variables on the change in the dependent variable with difference models. Other panel models, such as the dynamic probit model proposed by Wooldridge (2005), can be used to investigate state persistence, or the likelihood of remaining in a state, given an individual's previous state and is often used to investigate employment scarring. However, standard panel data models are not designed to model change over time though there are extensions that permit this (Andreß, Golsch, and Schmidt 2013, 201–202).

However, as our main interest is to describe trajectories of vulnerability to unemployment – or the latent risk of experiencing unemployment – and differences between individuals over time, growth curve models are a better 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 (Chou, Bentler, and Pentz 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 2016, 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 2016, 341).

4.1.1 Model Specification

Mathematically, a latent growth curve model can be expressed as follows in the structural equation framework[1]:

$$y_i = \Lambda\eta_i + \epsilon_i = \Lambda(\mu + \zeta_i) + \epsilon_i \tag{1}$$

where 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 cateogry of interest $y^* = 1$:

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

This is the basic equation for a growth curve model. The Λ matrix and the η_i vector change according to the specified model. The Λ matrix contains the loadings – the time scores – for the latent factors that describe the trajectory of change over time for the dependent variable. The η_i vector can be decomposed into two other vectors: the μ 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 μ vector describes the average trajectory of vulnerability to unemployment while the ζ_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 μ, ζ_i, and η_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 Λ matrix containing the factor loadings (time scores) and the μ and ζ_i

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

vectors are:

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

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.

The above model specifications show *unconditional* latent growth curve models, that is without the inclusion of any covariates. It is possible to add time-invariant covariates (TICs) thus extending the model to 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:

$$y_i = \Lambda\eta_i + \epsilon_i = \Lambda(\mu + \zeta_i + \Gamma_x x_i) + \epsilon_i \tag{2}$$

Compared to equation 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.

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.

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 full-information maximum likelihood estimation 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 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 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. 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 2016, 95).

5.1 Switzerland

Looking at the intercept factor means in Table 1, the estimates suggest a very low overall vulnerability to unemployment. 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 to unemployment. 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 to unemployment. What's more interesting is that over time, individuals who were initially out of employment or unemployed become less vulnerable to unemployment relative to those who were in employment. 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. 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 to unemployment. Thus, in the time since the crisis, vulnerability to unemployment 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 to unemployment which is 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 would become less vulnerable to unemployment 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 vulnerable to unemployment. Nevertheless, there would seem to be a trend of lower educated individuals being more vulnerable to unemployment.

	(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 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

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 to unemployment over time in Switzerland.

5.2 United Kingdom

The estimates for the latent factor means (Table 2) suggest a low overall vulnerability to unemployment which was also the case for the Swiss results. 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 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. 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 to unemployment.

As for the different age groups, individuals in the two youngest age groups were overall more vulnerable to unemployment which is in line with Hypothesis 2a. For those that were youngest, 18–24 in 2007, we also find that they became less vulnerable to unemployment over time. The trend for the 25–34 age group is similar, however the estimates are not significantly different from zero. These results are also in line with Hypothesis 2b which stated that younger individuals would become less vulnerable to unemployment over time.

	(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 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

Interestingly, we find that individuals who were in the oldest age category (45+) in 2007, became *more* vulnerable to unemployment over time relative to the reference age group. 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 to unemployment relative to those with an upper secondary level of education. Additionally, tertiary educated individuals were initially less vulnerable than those with an upper secondary level of education. As for differences in vulnerability over time – Hypothesis 3b – individuals with less than an upper secondary level of education became more vulnerable to unemployment over time. There is however no notable difference in change over time between the upper-secondary and tertiary levels.

6 Discussion & Conclusion

This paper 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 vulnerable to unemployment, 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 3: Hypotheses by Country

As for sociodemographic differences, we find that in Switzerland women were overall more vulnerable to unemployment than men 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 to unemployment 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 to unemployment over time relative to men. 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 over time. 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 vulnerable to unemployment 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 to unemployment over time, and this result 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 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 to unemployment over time 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 and Bandalos 2001) we should still be wary of attempting to generalise 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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A Descriptive Statistics

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 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 A.2: Descriptive statistics for covariates (measured in 2007)

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 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 A.4: Descriptive statistics for covariates (measured in 2007)

B Model Information Criteria

	Log-likelihood	AIC	BIC	*df*	*N*
Model 0	-1767.361	3544.723	3575.783	5	3685
Model 1	-1691.587	3401.175	**3457.083**	9	3685
Model 2	-1687.933	3397.866	3466.198	11	3685
Model 3	-1673.826	**3381.651**	3487.256	17	3685
Model 4	-1670.103	3382.206	3512.658	21	3685

Table B.1: Information Criteria SHP Models
Minimum in bold

	Log-likelihood	AIC	BIC	*df*	*N*
Model 0	-5296.286	10602.57	10636.88	5	7058
Model 1	-4734.056	9486.112	9547.869	9	7058
Model 2	-4721.975	9465.951	9541.432	11	7058
Model 3	-4705.322	9444.643	9561.296	17	7058
Model 4	-4614.024	**9270.049**	**9414.149**	21	7058

Table B.2: Information Criteria Combined BHPS & UKHLS Models
Minimum in bold