Measuring Resilience to Major Life Events

Fabrice Etilé*, Paul Frijters**, David W. Johnston*** and Michael A. Shields***

* *Paris School of Economics and INRAE*

** *Social Policy, London School of Economics*

*** *Centre for Health Economics, Monash University*

Version: 7^{th} July 2021

Abstract

There is great interest in understanding who in the population is resilient in the face of major life events, and who is not. In this paper we construct a revealed measure of adulthood psychological resilience by modelling individuals' responses to ten adverse life events using a dynamic finite mixture regression applied to 17 years of panel data. Our methodology accounts for non-random selection into events, and differences between individuals in anticipation, immediate response, and speed of adaptation. We find considerable heterogeneity in individuals' responses to events such as major financial shocks, redundancy and bereavement. We also find that our measure of resilience is correlated with clinical measures of mental health, and that it significantly predicts the psychological response to out-of-sample events. The strongest predictor of our measure of resilience is internal locus of control, which is an individual's belief that life outcomes are under their control.

Keywords: Resilience, Psychological Health, Major Life Events, Panel Data, Mixture Model

JEL: I10, C2, C5

We are grateful to the Australian Research Council for helping to fund this research, and to seminar participants at the London School of Economics and the Paris School of Economics for valuable comments. We are also grateful to Andrew Jones for comments. This paper uses unit record data from the Household, Income and Labour Dynamics in Australia (HILDA) Survey. The HILDA Project was initiated and is funded by the Australian Government Department of Social Services (DSS) and is managed by the Melbourne Institute of Applied Economic and Social Research (Melbourne Institute). The findings and views reported in this paper, however, are those of the authors and should not be attributed to either DSS or the Melbourne Institute.

1. Introduction

Talk about resilience is widespread nowadays. Internet web searches for "Resilience and Government" provide countless examples of national and local governments highlighting the importance of resilience in individuals, communities, and businesses. The COVID-19 crisis has further raised the importance of increasing resilience (Habersaat et al., 2020). Many governments have dedicated departments, units, advisory groups, forums and online portals aimed at providing information and training to improve resilience. The idea of building resilient communities is now a strategic goal of many national governments (see Longstaff et al., 2010; Cutter et al., 2013). Examples include the UK Government's Community Resilience Framework[1], and Public Health England's (2014) focus on building the resilience of children at school.[2] Fletcher and Sarkar (2013) suggest that governments should provide community-based opportunities that enable individuals to access environmental and personal resources that develop resilience.

There are many definitions of psychological resilience, but a prominent one is provided by Bonanno (2004), who defines it as the ability of individuals "who are exposed to an isolated and potentially highly disruptive event…. to maintain relatively stable, healthy levels of psychological and physical functioning." For individuals, building resilience is important because nearly everyone will experience at least one major adverse event at some point in their life, such as divorce, redundancy, worsening finances, serious injury, being a victim of crime, or the death of a partner or close friend. Individuals and communities may also be victims of natural disasters, civil conflict, or such criminal acts as mass shootings and terrorism. The questions then arise: how well do individuals cope with such events, and who are the most and least resilient individuals?

From an economics perspective, providing new evidence on these questions is a valuable research task as resilience can be thought of as a form of self-insurance. Therefore, as noted by Clark (2016), "The analysis of the distribution of resilience is of policy importance, as it would help to show us who needs more help, and in what circumstances." Cunha and Heckman (2009) stress the importance of research that can identify the mechanisms that promote resilience and recovery from disadvantage, noting a lack of systematic knowledge in this area. Similarly, Asheim et al. (2019) note that, "There does not seem to be much of a literature within economics when it comes to the measurement of individual resilience. This is somewhat surprising because there appears to be a clear link between resilience and individual and social well-being—and the high economic costs associated

[1] See: https://www.gov.uk/government/publications/community-resilience-framework-for-practitioners.

[2] Moreover, in recent decades, large-scale training programs for children, adults and teachers have emerged that aim to increase 'resilience', including the Penn Resilience Program (https://ppc.sas.upenn.edu/research/resilience-children), the UK Grit Program (www.grit.org.uk), and Australia's Resilient Youth (www.resilientyouth.org.au). Similarly, there are 'resilience courses' for emergency service workers (e.g. www.mind.org.uk), and the Rockefeller Foundation 100 Resilient Cities network (www.100resilientcities.org) is an example of a broad vision for resilient communities.

with mental illness." Moreover, a recent high profile review by leading resilience researchers in psychology explicitly calls for more, "research on the dynamic processes of successful adaption to stressors in prospective longitudinal studies" (Kalisch et al., 2017).

Resilience can be measured in different ways, from scales derived from asking people about their beliefs about their own resilience (stated-resilience)[3], to measures based on observing the response of individuals to particular types of events (revealed-resilience). The approach we take is based on observing (thus revealed) how a large nationally-representative sample of adults respond to the experience of many different types of adverse events.[4] To do this we develop a dynamic finite mixture model applied to 17 waves of data. Rather than narrowly focussing on one type of event, we establish the extent of individual heterogeneity in the response to ten major adverse events ranging from a worsening financial event, bereavement and crime victimisation. This modelling approach builds on the latent class and finite mixture approaches used by economists (e.g. Clark et al., 2005; Etilé, 2006; Bruhin et al., 2010; Conte et al., 2011; Brown et al., 2014; Etilé and Sharma, 2015; Cuaresma et al., 2016; Eckardt et al., 2016; Bacci et al., 2019; Bruhin et al., 2019; Carrieri et al., 2020), and on the latent growth mixture modelling approach used by psychology researchers (e.g. Bonanno et al., 2010; Galatzer-Levy et al., 2010; Mancini et al., 2011; Galatzer-Levy and Bonanno, 2012; Baron et al., 2017; Phelps et al., 2018; McGiffin et al., 2019).[5]

Like Cunha and Heckman (2009) and Schurer (2017) for example, we take resilience to be a non-cognitive skill largely developed in childhood (Cunha et al., 2010), where we expect the benefits in later life to be (i) lower amplitude following negative life events and, (ii) faster adaptation.[6] The model we use allows for heterogeneity in both anticipation and adaptation responses, while accounting for the initial conditions problem and selection into events on fixed unobservable

---

[3] There are many such proposed resilience scales, which are based on questions about beliefs asked to individuals about whether, for example, they believe that they are self-disciplined, usually take things in their stride, are determined, can adapt when changes occur, can deal with whatever comes their way, can find things to laugh about, or that their life has meaning. Two such scales are the Wagnild Resilience Scale RS-14 (Phillips et al., 2016), and the Connor-Davidson Resilience Scale (Connor and Davidson, 2003).

[4] We would suggest that it is unlikely that revealed resilience can be measured well in experimental laboratory settings, as individuals need to experience major life events and be observed in the years before and after the event.

[5] Most papers in the resilience literature tend to focus only on one event. Some examples are on: bereavement, divorce (Mancini et al., 2011), chronic pain (Zhu et al., 2014), disability (McGiffin et al., 2019), injury (Bonanno et al., 2012), the 9/11 New York attack (Bonano et al., 2006, 2007; Norris et al., 2009), mass shootings (Norris and Stevens, 2007; Reifels et al., 2013), floods (Norris et al., 2009), oil spills (Lee et al., 2018), droughts (Arouri et al., 2015), earthquakes (Hogg et al., 2016), and epidemics (Rao and Greve, 2017). Many studies have focused on the resilience of war veterans (Pietraz et al., 2009; Tsai et al., 2015; Portnoy et al., 2018).

[6] Relatedly, Borghans et al. (2011) discuss the difficulty with identifying psychological constructs, where they are often measured by observed behaviours including observer reports and test scores. They argue that behaviours are the result of incentives, and various psychological constructs (traits, attitudes, etc.). Hence, in order to isolate a single psychological construct, researchers need to control for the influence of all other constructs and incentives. In this paper, compared to measures of resilience that would be based on purely hypothetical item questionnaires (such as the CD-RISC scale), we innovate by using ecological data where people are "naturally incentivised" by major life events, and we control for selection into such events.

characteristics. Resilience is measured as the total psychological loss (TPL) from an event, and we also provide an overall measure based on the response to a weighted sum of all events. It is important to include anticipation effects in our measure because many major life events such as being made redundant, becoming separated or divorced, and death of a family member or close friend, are often foreseeable. We think of resilience in this context as potentially being driven by two components. Firstly, we will observe a smaller TPL (more resilient) for those who have little psychological response to life events. Secondly, we will observe a lower TPL through behaviour: for those who actively find ways to tackle the adversity. An example of the latter would be increased job search following redundancy. Importantly, our model allows for substantial heterogeneity in TPL profiles.

We analyse data from the Household, Income and Labour Dynamics in Australia (HILDA) survey, which tracks respondents from 2001 to 2017. This survey is well suited to the task because it has followed a large sample over many years, and each wave it asks respondents about both their psychological health and the major life events they have experienced in the past 12 months.[7] The ten major life events we focus on are: a major worsening in financial situation; being fired or made redundant; separating from spouse or long-term partner; death of a spouse or child; death of other close relative or family member; death of a close friend; serious injury or illness to self; serious injury or illness to a close relative; being a victim of physical violence; and being a victim of property crime. Notably, some 96% of respondents report experiencing at least one of these adverse events within our panel window.

Our resulting estimates enable us to: (1) document the distribution of resilience, (2) distinguish the types of people who are the most and least resilient across the distribution, (3) test how strongly resilience is related to clinical measures of mental health, and (4) explore the distinctiveness of resilience from measures of cognitive and non-cognitive traits that have been the focus of a growing economics literature in recent years. We also document how strongly our 'revealed' measure of resilience is correlated with locus of control (a 'stated' belief), which has been the focus of economic studies of behaviour (e.g. investment, saving, job search, health investments). We find a strong correlation between resilience and locus of control across the entire resilience distribution.

2. Empirical strategy and methods

We develop a dynamic finite mixture model to identify individual heterogeneity in the observed fluctuations in psychological health that follow major life events. We also derive an individual-specific measure of resilience based on total psychological loss (TPL) from a "standardised event"

[7] In providing an integrative framework for studying resilience, Bonanno et al. (2015) argue that studies must explicitly reference four temporal elements: baseline or preadversity functioning, the actual aversive circumstances, postadversity outcomes, and predicts of resilient outcomes. Data from HILDA allows for all of these.

(SE). We then investigate the strength of the relationships between our measure of resilience and clinical measures of mental health, as well as age, gender, educational attainment, cognitive ability, Big-5 personality traits, and locus of control.

2.1 Modelling the dynamics of psychological health: A finite mixture dynamic approach

Before introducing our main model of psychological health (H_{it}), we discuss a standard dynamic model in which the effects of adverse events are presumed to be identical for all individuals:

$$H_{it} = \rho H_{it-1} + \beta' x_{it} + \mu S_{it} + \delta_i + \tilde{\varepsilon}_{it} \qquad (1)$$

where S_{it} is a vector of major adverse events, x_{it} is a set of socioeconomic variables that control for current life circumstances, δ_i is an individual effect, and $\tilde{\varepsilon}_{it}$ is a serially uncorrelated error term. Lagged psychological health captures the lasting effect of past events on current psychological health, discounting all adverse events at the same exponential rate, ρ. In this model, psychological health follows a first-order Markov process, whereby psychological health at *t* is independent from psychological health at *t-2*, and from past life events, past observed covariates and past time-varying shocks, conditional on psychological health at *t-1*, life events and observed covariates at *t*, and individual time-invariant heterogeneity. Our specification is consistent with previous empirical studies that have focused on the impact of lagged adverse events and the extent to which individuals adapt over time (e.g. Lucas et al., 2004, 2005; Clark et al., 2008; Oswald and Powdthavee, 2008; Frijters et al., 2011; Kettlewell et al., 2020). A point of difference, however, is that instead of including lags of the event variables (e.g. S_{it-1}, S_{it-2}, S_{it-3}) in a static model, we include lagged psychological health. This is similar to the approach taken by Pudney (2008), in which a dynamic specification is used to model individuals' subjective assessments of their financial wellbeing. Pudney (2008) interprets the presence of the lagged dependent variable in terms of partial adjustment of perceptions to changes in current life circumstances.

Our model builds on this approach by adding heterogeneity in the anticipation of, and response to, major life events through the introduction of random coefficients, and by allowing the error-term variance to be individual-specific:

$$\begin{aligned} &H_{it} = \rho_i H_{it-1} + \beta' x_{it} + \mu_{i0}' S_{it} + \mu_{i1}' S_{it+1} + \delta_i + exp(\sigma_i)\tilde{u}_{it} \\ &\tilde{u}_{it} \sim \text{i.i.d normal}(0,1) \end{aligned} \qquad (2)$$

where the coefficients ρ_i, μ_{i0}, μ_{i1}, δ_i and σ_i are individual effects. The immediate impacts of events on psychological health are represented by the parameter vector μ_{i0}, while the anticipation effects are captured by μ_{i1}. This specification controls for selection into life events on fixed unobserved heterogeneity, and we only assume that conditional on δ_i, life events randomly befall on individuals. We thus control for non-random selection into life events, under the particular assumption that the occurrence of life events after *t+1* is independent from psychological health at *t*, conditional on life events occurring at *t* and *t+1*, observed covariates at *t*, and δ_i.[8]

The empirical literature documenting the impact of life events on wellbeing has largely focused on adaptation (post-event) profiles, but Clark et al. (2008), Frijters et al. (2011) and Kettlewell et al. (2020), and others, have shown that wellbeing measures also change prior to the occurrence of events. They have found that the events with the strongest anticipation effects are those that are understandably predictable, such as divorce. In our model, the individual-specific anticipation parameter μ_{i1} measures the impact of all information relevant to future events that the respondent has already received. Observed future events are thus included as proxy variables for this information.

Importantly, Equation (2) allows individuals to differ along four key dimensions: (1) baseline level of psychological health due to unobserved time-invariant factors as accounted for by δ_i: this can be interpreted as an individual set-point to which a person returns in the long run, but is included to capture any heterogeneity in levels that is constant over the data period (we refrain from interpreting its determinants causally); (2) anticipation and immediate (short-term) reactions to each life event, as accounted for by the parameter vectors μ_{i0} and μ_{i1}; (3) average adaptation trajectories, as captured by ρ_i, with a higher ρ_i implying slower adaptation; and (4) unobserved events that may vary in frequency and magnitude across individuals, as accounted for by σ_i, which captures unobserved volatility in psychological health.

The dynamic nature of equation (2) means that we face an initial condition problem, because the first observed level of psychological health could be correlated with the individual effects. We overcome this issue by conditioning on initial psychological health H_{i0}, specifying a Mundlak-type relationship between the individual effect δ_i and the covariates:

$$E[\delta_i | H_{i0}, S_i, x_i] = \alpha_i + \lambda w_i \tag{3}$$

where S_i and x_i are row vectors of all explanatory variables in all time periods, α_i is an individual individual random effect, and $w_i = (H_{i0}, \bar{S}_{it}, \bar{x}_{it})$. We also assume that $(\rho_i, \mu_i, \sigma_i)$ are independent of the covariates. Therefore, our measure of individual heterogeneity in adaptation to life events will not

[8] This then excludes specific sequences, for instance the case where a depression at *t* increases the probability of divorce at *t+2*, even after controlling for other life events occurring at *t* and *t+1*. As we chose to work with a large set of life events, it is not practically possible to model and identify the probabilities of occurrence of all the life events. This would have required the identification of 2^{10}-1 probabilities of transition, and therefore the availability of many unrelated exclusion restrictions to identify these probabilities.

reflect individual ability to affect the occurrence of events (self-selection).[9] The parameter vector $\Theta_i = (\rho_i, \mu_i, \alpha_i, \sigma_i)$ is distributed according to a joint density function $f(\Theta_i)$ that can be factored into a conditional distribution $g(\alpha_i, \sigma_i, \rho_i|\mu_i)$ and a marginal distribution $h(\mu_i)$.

We assume that g and h are finite discrete distributions.[10] We therefore let the marginal density h be represented by a finite number C of points $\{\mu_1, \mu_2, \ldots, \mu_C\}$ with associated mass probabilities $\{p_1, p_2, \ldots, p_c\}$. Hence:

$$Pr(\mu_i = \mu_c) = p_c, \sum_{c=1}^{C} p_c = 1 \tag{4}$$

Letting $\theta_i = (\alpha_i, \sigma_i)$, the conditional distribution $g(\theta_i, \rho_i|\mu_i)$ is represented by a bivariate discrete distribution with $K_c \times L_c$ support points $\{(\theta_{kc}, \rho_{lc}); k = 1, \ldots, K_c; l = 1, \ldots, L_c\}$ and associated mass probabilities $\{\pi_{klc}; k = 1, \ldots, K_c; l = 1, \ldots, L_c\}$:

$$Pr(\theta_i = \theta_{kc}, \rho_i = \rho_{lc}|\mu_i = \mu_c) = \pi_{klc}, \sum_{k=1}^{K_c} \sum_{l=1}^{L_c} \pi_{klc} = 1 \tag{5}$$

The literature often takes a 'latent class' interpretation of these distributional assumptions[11], whereby the heterogeneity of the population results from the mixing of several populations (classes) that may differ in their short-term (μ_c) and long-term (ρ_{lc}) responses to life events, and in the baseline level and volatility of psychological health (θ_{kc}). With individual class membership unobserved, these population classes are latent. We view this 'latent class' interpretation of the model as a convenient way to discuss the estimation results. Notably however, the latent classes only capture 'ideal' types of psychological response profiles, with all individuals lying somewhere between these ideal classes. Our ultimate aim is to identify individual profiles of responses to adverse events through a mixture of these types. Conditional on time-invariant membership in a latent class indexed by $\{c,k,l\}$, the dynamics of psychological health are assumed to be represented correctly by the following model with non-random and fixed coefficients:

$$\begin{aligned} H_{it} &= \rho_{lc} H_{it-1} + \beta' x_{it} + \mu_{0c}{}' S_{it} + \mu_{1c}{}' S_{it+1} + \lambda w_i + \alpha_{kc} + exp(\sigma_{kc}{}')\tilde{u}_{it} \\ \tilde{u}_{it} &\sim \text{i.i.d normal}(0,1) \end{aligned} \tag{6}$$

---

[9] The assumption of independence between $(\rho_i, \mu_i, \sigma_i)$ and (H_{i0}, S_i, x_i) could be relaxed. But this would come at the price of introducing many interaction terms between the covariates, and therefore losing all the benefits of mixture models.

[10] We have chosen discrete distributions for the parameters instead of continuous multivariate distributions to gain in flexibility, to minimize specification biases – discrete distributions can approximate any continuous distribution - and to avoid having to use simulated maximum likelihood techniques with high-dimensional integrals.

[11] For instance, Clark et al. (2005) present their model in terms of latent classes, rather than using the more general term "finite mixture". A similar presentation has often been used in the empirical literature on health care use (Deb and Trivedi, 2002) or consumption (Wedel et al., 1993; Etilé, 2006).

Importantly, this finite mixture dynamic model allows individuals with similar short-term responses to adverse events to have different speeds of adaptation: the correlation between the distribution of ρ_i and the distribution of μ_i is not restricted *a priori*. In addition, the dependence between heterogeneity in response profiles, and the heterogeneity in levels and unobserved volatility of psychological health, is left unrestricted. This would not have been the case if we had restricted the distribution of $\theta_i = (\alpha_i, \sigma_i)$ to have only one support point (i.e. we do not impose $K_c=1$ for all c).[12] As such, we will identify resilience heterogeneity from individual patterns of reactions to the adverse events specified in S_{it}, not from the size of unobserved shocks captured by σ_i.[13]

2.2. Measuring resilience as psychological loss

After estimating the finite mixture dynamic model, we derive individual-specific values of the parameters that govern individual differences in psychological responses to life events. We then construct individual measures of resilience, and examine how they correlate with clinical measures of mental health, as well as pre-determined age, gender, educational attainment, and measures of cognition and personality.

To formalise resilience, we first define a measure of 'Total Psychological Loss' (TPL) for a set of standardised events $S_{.t}=s$ occurring at time t. A natural choice for the standardised events is the average in the sample, i.e.$s = \overline{S_{it}}$. For any individual, TPL then equals:

$$TPL_i(s) = -\sum_{s=t-1}^{+\infty}(H_{.s}(.,S_{.t} = s, \tilde{u}_{.t} = 0; \rho_i, \mu_i) - H_{.s}(.,S_{.t} = 0, \tilde{u}_{.t} = 0; \rho_i, \mu_i)) \qquad (7)$$

where $H_{.s}(.,S_{.t} = s, \tilde{u}_{.t} = 0; \rho_i, \mu_i)$ denotes the psychological health of an individual whose life trajectory is only changed with respect to the events that happened in period t.[14] TPL measures inter-individual differences in the undiscounted lifetime impact of adverse events, holding constant the probability of experiencing adverse events. Given the linear nature of our model, TPL is independent of any other characteristics or history and collapses to a simple formula:

---

[12] This constraint, which is almost always imposed in empirical applications of latent class models, would imply that all healthy individuals show little reaction to adverse events, while all unhealthy individuals are very reactive (or vice versa). To relax this constraint, we increase the number of classes, but restrict the slope parameters to be similar across some classes. We then have subsets of classes with similar slope coefficients, but different intercepts. Also, unrestricting the potential number of intercept classes gives us more flexibility in modelling the correlated random effect δ_i.

[13] Appendix B provides additional details regarding the likelihood function, the identification, the inference procedure and the selection of the optimal number of classes. Eventually we retained a specification with C=3 and $L_1=L_2=L_3$=1, and $K_1=K_2=K_3$=9.

[14] In this paper we focus on resilience in terms of the reactions to negative life events. The minus sign is set to yield a scale taking positive values, as the psychological impact of negative life events is negative a priori. The unobserved shocks are set to 0, because we want to avoid any influence of the variance σ_i, which captures volatility due to both positive and negative shocks.

$$TPL_i(s) = -\frac{(\mu_{i0}+\mu_{i1})s}{1-\rho_i} \quad (8)$$

Individual values for *TPL* can be obtained by using the estimated model coefficients. To see how it works, note that for each individual *i* we can compute the set of posterior probabilities from the model estimates:

$$\begin{aligned} p_{icl} &= \Pr(\rho_i = \rho_{lc}, \mu_i = \mu_c | H_{i1}, \dots H_{iT}, S_i, x_i, H_{i0}, w_i, \beta, \lambda) \\ &= \sum_{k=1}^{K_c} \Pr(\rho_i = \rho_{lc}, \mu_i = \mu_c, \theta = \theta_{kc} | H_{i1}, \dots H_{iT}, S_i, x_i, H_{i0}, w_i, \beta, \lambda) \\ &= \sum_{k=1}^{K_c} \frac{p_c \pi_{klc} \Pr(H_{i1}, \dots H_{iT} | S_i, x_i, H_{i0}, w_i, \rho_i = \rho_{lc}, \mu_i = \mu_c, \theta = \theta_{kc}, \beta, \lambda)}{\Pr(H_{i1}, \dots H_{iT} | S_i, x_i, H_{i0}, w_i, \beta, \lambda)} \end{aligned} \quad (9)$$

These membership probabilities then can be used to construct expected individual values for *TPL*, conditional on the available information:

$$TPL_i^*(s) = E(TPL_i(s) | H_{i1}, \dots H_{iT}, S_i, x_i, H_{i0}, w_i, \beta, \lambda) = \sum_{c=1}^{C} \sum_{l=1}^{L_c} p_{icl} TPL_{lc}(s; \rho_{lc}, \mu_c) \quad (10)$$

where $TPL_{lc}(s; \rho_{lc}, \mu_c)$is a measure of *TPL* for resilience class *{c,l}*:

$$TPL_{lc}(s; \rho_{lc}, \mu_c) = \frac{(\mu_{c0}+\mu_{c1})s}{1-\rho_{lc}} \quad (11)$$

In a second step, we can estimate the extent to which adulthood fixed characteristics (e.g. gender, educational attainment, cognition) predict resilience.[15]

3. Data

3.1. The Household, Income and Labour Dynamics in Australia (HILDA) Survey

We use data from the HILDA Survey, a nationally representative longitudinal study of Australian households that began in 2001. Wave 1 began with a sample of 19,914 panel members from 7,682

[15] We do not estimate this second step as an integral part of the latent class modeling of the dynamics of psychological health, because we want to avoid imposing strong priors on the nature of the correlates of resilience. In this second-step regression, the dependent variable is a complex and non-linear functional form of the first-stage estimates. This introduces heteroskedasticity in the regressions. We therefore apply a White correction in all of our second-stage regressions (White, 1980). More efficient techniques that are advocated in the context of linear transformations of first-stage estimates cannot be used here (Hanushek, 1974; Saxonhouse, 1976). Consequently, our second-step results will tend to yield over-estimated standard errors.

households. In each year since, members of these households have been followed-up, along with new household members that result from changes in the composition of the original households, and new households from the Wave 11 top-up sample. Our data are from 2001 to 2017, with each wave providing detailed information on a wide-range of economic, demographic, social and health measures.

For our analysis, HILDA has the advantage of including: questions asked in every wave about whether respondents' experienced a wide range of major life events in the last twelve months; respondents are followed over a long enough period of time for us to be able to capture anticipation and adaptation; a detailed and consistent health survey is conducted in every wave (i.e. the SF-36 questionnaire); we know whether individuals have a diagnosed mental health condition, and whether they are taking medication; respondents have been tested on their cognitive ability (Wave 12); personality traits have been collected through the Big-5 Personality Inventory (Waves 5, 9, 13 and 17) and a locus of control questionnaire (Waves 3, 4, 7, 11 and 15). All demographic and socioeconomic information are collected through face-to-face interviews, while information on life events, health, and personality, are collected through a confidential self-completion questionnaire. We are unaware of any other panel survey that contains all of this required information.

We focus on respondents who were aged 25 to 69 in their first survey. Importantly, we exclude those respondents who are observed for less than eight consecutive periods, which we take to be a sufficient time period to observe the full adaptation profile of most life events, and the time we find is required for the within-individual variance in psychological health to stabilise (results available upon request). Finally, we exclude observations with missing information on the life event variables. Given that the life event questions were not included in Wave 1 of HILDA, this restriction means that equation (1) is estimated using information from Waves 2-17. However, Wave 1 psychological health is used to address the initial conditions problem (as noted in Section 2.2). These combined restrictions leave us with the main estimation sample of 6,294 individuals and 69,460 individual-period observations.

3.2. Measuring psychological health

Psychological health is a latent variable that we measure using information from the Short-Form General Health Survey (SF-36), which is incorporated in many surveys and asks respondents a wide-range of questions about their health. Let H_{it} denote the true latent psychological health of individual *i* at time *t*, and assume H_{it} is related to a set of *K* survey indicator variables $I_{it}^1, \ldots, I_{it}^K$ by a measurement function $\mathcal{M}$:

$$\left(I_{it}^1,\ldots, I_{it}^k\right) \rightarrow H_{it} = M(I_{it}^1,\ldots, I_{it}^k).$$

Following international guidelines (Ware, 2000), the measurement function $\mathcal{M}$ is a factor analysis model of the eight health dimensions of the SF-36. These eight dimensions are constructed by a weighted summation of answers to items on the SF-36 and cover the main domains of health: physical functioning, physical role functioning, bodily pain, general health perception, vitality, social functioning, emotional role functioning and mental health. The factor analysis uses only the first observation of each individual in the full sample of HILDA, and produces a two-component representation: the first component summarises psychological health (eigenvalue equals 2.394) and the second component summarises physical health (eigenvalue equals 2.060). Column 1 of Table A1 in Appendix A reports the factor loadings of each of the eight dimensions on the psychological health component. The second column reports the coefficients of the linear equation used to predict the psychological health component after orthogonal Varimax factor rotation. These coefficients show that psychological health primarily reflects four dimensions of the SF-36: mental health, emotional functioning, social functioning, and vitality. The psychological health component is normalised to have a mean of 50 and a standard deviation of 10 in the full HILDA sample, yielding the psychological health observations used to estimate equation (1).[16]

Figure 1 shows a histogram of psychological health for the estimation sample. The distribution has a mean of 51.2 and a standard deviation of 9.48. It is negatively skewed (skewness equals -1.2) and leptokurtic (kurtosis equals 4.4). While the vast majority of individuals are in good psychological health, 10% of the observations have scores lower than 38, and 5% of the observations have scores lower than 32.

3.3. Major life events

A key advantage of the HILDA survey is that in every wave (starting in wave 2) respondents are asked about the occurrence of major life events (in a section of the confidential self-completion questionnaire). This section is completed after the SF-36 health questionnaire, so respondents' recollection of life events should not bias their evaluation of their psychological health. Respondents are told, "We now would like you to think about major events that have happened in your life over the past 12 months", and then are asked to indicate whether each of the listed events happened and

[16] Note that simultaneously estimating the measurement model and the finite mixture dynamic model for latent psychological health is not feasible. Pudney (2008) applies a simulation method for estimating a dynamic model of subjective wellbeing similar to (1), wherein the measurement model is specified with ordered probit models. This involves simulating integrals of dimension equal to the number of observation periods plus one, so the data is restricted to six periods. In our case, the identification of individual heterogeneity in parameters requires that a maximum number of periods be used. In addition, the estimation and the selection of latent class models rely on an iterative EM algorithm, with the maximisation of likelihood functions at each step (see Appendix B).

how long ago.[17] The list has been expanded over the waves to 21 life events, but we focus in this paper on the following ten more commonly experienced adverse events: (1) "major worsening in financial situation (e.g. went bankrupt)"; (2) "fired or made redundant by an employer"; (3) "separation from spouse or long-term partner"; (4) "death of spouse or child"; (5) "death of other close relative / family member (e.g. parent or sibling)"; (6) "death of a close friend"; (7) "serious personal injury or illness to self"; (8) "serious personal injury or illness to a close relative / family member"; (9) "victim of physical violence (e.g. assault)"; and (10) "victim of a property crime (e.g. theft, housebreaking)".

Table 1 provides descriptive characteristics for each of these events, with 96.3% of respondents in the estimation sample reporting at least one of them in the panel window, a median of four events and 34.1% having six events or more. Moreover, we have a non-trivial number of occurrences for each of these events, with 'serious injury/illness to family member' being the most common, occurring in 16.4 percent of the year-person observations, or once every 6 years for the average individual. This is followed in frequency by 'death of a relative / family member' and then 'death of a close friend', which are reported in around 11 percent of the year-person observations. A major worsening of finances, being fired or made redundant, being a victim of property crime, and becoming separated from spouse or partner are all reported by around 2 to 4 percent of cases. As expected, the least common events are 'death of spouse/child' and 'victim of physical violence', with less than one percent of the sample reporting such an event.

3.4. Sample characteristics

Table 1 also shows the average of the contemporary covariates used in our analyses. The average age of the sample is 51; 47 percent of observations are male; and 47 percent are employed full-time, with around 2 percent being unemployed. Just under one-third (28 percent) have a university degree-level education, the log of annual household income is 11.08; 78 percent are married or cohabitating; and the average number of dependent children is 0.60. Additionally, we present descriptive statistics for the cognitive and non-cognitive (personality) traits, as well as alternative clinical-related indictors of psychological health, which we use later to inform the resilience measure. Importantly, one-in-ten of the observations in our sample report a current diagnosis of depression and/or anxiety; around 5 percent are taking prescription medication(s) for these conditions; and just under 6 percent report having seen a psychiatrist or psychologist in the past year.

[17] While respondents are asked about the timing of these adverse events in terms of 3-month periods (0-3 months ago, 4-6 months ago etc.), we focus only on annual data in this paper as the time profiles we find are clear. See Frijters et al. (2011) for an application using this data.

4. Results

4.1. Resilience: Psychological response to major adverse events

Our main results are presented in Table 2. Column 1 shows the estimates from a dynamic random effects (DRE) model that controls for initial conditions but only provides information about the average response to events, because there is no heterogeneity in coefficients (see Equation 1 with the same parameters for all individuals). The results from this initial model are informative and appear reasonably intuitive. First, the coefficient on lagged psychological health (0.219) tells us that, for the sample as a whole, there is a fairly low level of persistence over time. Second, all of these major adverse events are associated with a significant immediate decline in psychological health. As expected, the effects are large for death of a spouse or child (-2.678), separation from spouse or partner (-2.150), injury or illness to self (-2.412), and being a victim of violent crime (-1.995). Interestingly, the second largest immediate decline in psychological health, after the death of a spouse or child, arises from a major worsening of financial situation, such as a bankruptcy (-2.780). In contrast, there is only a relatively small immediate response from having been fired or made redundant (-0.331). The model also reveals that many of these adverse events are anticipated before their actual occurrence. The largest anticipation effects occur for separation from spouse or partner (-1.417) and death of spouse or child (-1.229). The economic events major financial worsening (-0.749) and being fired or made redundant (-0.509) are also anticipated. In contrast, the only events for which we find no significant evidence of anticipation effects are death of a close relative, or death of a close friend.

Results from our preferred specification (Equation 2) are shown in Columns 2-4 in Table 2.[18] This model captures heterogeneity in psychological response by identifying three distinct slope 'classes' of individuals, each describing about one-third of our sample (the split is 37.5%, 28.7% and 33.6%). It is clear from the estimates that this model allows for greater insight into how individuals differ in their responses to commonly experienced adverse events. The event variables were all significant in the DRE linear model, but these estimates reflect average effects and hide considerable heterogeneity in the population. In particular, it is clear that the coefficients on the event variables are much larger for Class 3 than for Class 2, and to a lesser extent (but not in all cases) are higher for Class 2 than for Class 1. For instance, the immediate effect of a separation from spouse or partner equals -4.766 for Class 3, -0.311 for Class 2, and –0.288 for Class 1. We also find large differences in the speed of adaptation between the three classes. The effect of previous psychological health is markedly higher for Class 2 (0.465) than for Classes 1 (0.115) and 3 (0.136). These estimates imply

[18] The control variable coefficients from our finite mixture model are shown in Appendix Table A2. However, they are difficult to interpret because they are related to the probability of belonging to each of the three classes and the initial conditions variables.

that adaptation is nearly complete within one year for Class 1 and 3, with events having a half-life of around one year. The return to a baseline level of psychological health takes considerably longer for Class 2, with the reduction in psychological health after one and two years equalling 46.5% and 21.6% of the immediate drop, respectively. Notably, the small coefficients on the lag of psychological health for two out of the three classes relative to the DRE linear model estimate of 0.225, suggests that we have adequately controlled for individual heterogeneity in this model. Important unobserved heterogeneity would be reflected by large coefficients on the lagged psychological health variable.

The relative sizes of the estimated adverse event coefficients are in line with expectations. For Class 3, the death of a spouse or child is the worst event that we measure, with an immediate substantive drop (-9.687) in psychological health. Furthermore, experiencing a major financial worsening, separation from a spouse or partner, and own serious illness or injury, are all estimated to reduce psychological health by about a half-standard deviation in the short term (-4.910, -4.766, -5.161). For Class 3 the coefficients on the lead event variables (S_{t+1}) are largest for events that conceivably could be anticipated: the effect is significant for separation from spouse or partner (-2.288), death of spouse or child (-1.574), and injury or illness to self (-1.032).

In contrast to these results, the estimates for Classes 1 and 2 are generally smaller and more often statistically insignificant. Importantly though, these two Classes of individuals do react differently to life events. For Class 1, a major financial worsening (-0.528), death of a spouse or child (-0.552), death of a close relative (-0.149), injury or illness to self (-0.254) and being a victim of property crime (-0.428), are linked to a significant decline in psychological health. In fact, it is only for this class where we see a negative effect of property crime. Similarly, only for Class 1 do we see a small positive increase in response to being fired or made redundant (0.377), in complete contrast to the decline experienced (-1.119) by those in Class 3. Interestingly, for Class 1 we see a drop in psychological health in anticipation (-0.756) from a death of a spouse or child, but this effect is smaller (-0.552) on impact. In contrast, individuals in Class 2 experience a larger reaction to a major financing worsening (-0.942), death of spouse or child (-1.282), death of a close friend (-0.449), own injury to illness (-1.167), injury or illness of a relative (-0.496), and being a victim of physical violence (-1.411) than those in Class 1. It is only for being a victim of property crime that the psychological loss is larger at impact for individuals in Class 1 (-0.428) than Class 2 (0.265, not significant). Class 2 also experience larger anticipation effects for own injury or illness than Class 1. [19]

[19] We note that lagged effects in our model work through lagged psychological health. We have explored whether this is overly restrictive by estimating a model that includes lag variables of all events, in addition to lagged psychological health (see Appendix D). The estimates of Total Psychological Loss (TPL) by event using this approach are not significantly different from those derived using our main approach.

In the second half of Table 2 we present the estimation results for the intercept α_{kc} and error variance parameters σ_{kc} that are specific to each of the 27 latent classes $\{c,k\}$. These parameters account for individual heterogeneity in the baseline level of psychological health from unobserved fixed factors, as well as for unobserved shocks that may vary in size and impact across individuals. These estimates and the estimated autoregressive parameter ρ_{lc} fully characterise the unobserved heterogeneity in the process governing the dynamics of psychological health. Intuitively, the dynamics will depend on the importance of state-dependence on the one hand and on the frequency and impact of observed and unobserved shocks on the other hand.

We interpret these results by comparing the three slope classes indexed by c with a focus on the intercept-variance classes $\{k,c\}$ that weigh more than 1% in the finite mixture distribution (probability weight π_{kc}>1%). Class 1 (c=1, first column) generally has higher values for the intercept parameters, and the estimated variance parameters are much lower than the raw variance of psychological health, which is normalised to equal 10. Since Class 1 individuals also have a low estimated autoregressive parameter, which represents dynamics of psychological health that are characterised by little state dependence and small fluctuations around high baseline levels. In contrast, Class 2 (c=2) has the lowest estimated intercept parameters, and its variance parameters vary from 1.85 for c=2 and k=8 to 8.80 for c=2, k=2. The autoregressive parameter ρ is close to 0.5, so Class 2 captures the dynamics of psychological health that display large state-dependence and potentially large fluctuations from unobserved shocks. Class 3 (c=3) has higher intercept estimates than slope class 2, and larger estimates of the variance parameters (13.10 for c=3 and k=8; 7.86 for c=3 and k=9).[20] The estimated autoregressive parameter is low, implying that slope Class 3 represents a type of dynamics with little state-dependence and large fluctuations produced by unobserved shocks. Although the three slope classes eventually characterise different types of dynamics, there is still important heterogeneity within each slope class, as seen in the estimated intercept and variance parameters. This demonstrates the importance of separately modelling the heterogeneity in state dependence and the heterogeneity in unobserved shocks. In particular, two individuals may be similar in their ability to cope well with adverse events (little state-dependence), but they may still differ with regards to the impact of observed or unobserved events that they experience.

4.2. Graphical illustrations of response heterogeneity

[20] A convenient way of comparing the three classes is to predict the intercept and variance values of individuals in each 'slope class'. The average variance is 3.73 in Class 1, 4.85 in Class 2 and 6.66 in Class 3, while the average intercept is 31.44 in Class 1, 8.74 in Class 2, and 27.11 in Class 3.

Figure 2 illustrates the fit of the model and displays the extent of response heterogeneity by summarising the coefficients on the different intercepts and variances shown in Table 2. The left-side graph shows in grey the densities of psychological health for all of the different combinations of classes, intercepts, and variances, representing all of the possible shapes of the psychological health distribution that we allow via the finite mixture distributions. The bold curve represents the aggregate, empirical distribution of psychological health. In the second graph in Figure 2, we weight these different densities by the estimated relative probability weights of each combination, showing that extreme distributions with density near the tails have low weights, and therefore are less important in making up the whole population.

To illustrate how the coefficients on the lagged psychological health variable and the adverse life events collectively determine the psychological responses to different events, Figure 3 shows the response profiles for each of the Classes for a 'standardised event' (SE) - this is calculated as the occurrence-weighted average of all ten events (see equations (9) and (13) in Section 2.4). These profiles suggest that despite Class 3 adapting much faster than Class 2, the cumulative total drop in psychological health is greater for Class 3 because of its relatively large immediate negative response. The profiles also show that Class 2 has the second largest cumulative drop in psychological health, driven not by large immediate responses but rather by slower adaptation. The magnitudes of these psychological responses are moderate – the immediate response for Class 3 is around 10 percent of a standard deviation of psychological health.

Figure 4 provides psychological response profiles by Class separately for each event. These graphs show that the psychological loss for Class 3 is large for a major financial worsening, separation, death of spouse or child, own illness, and being a victim of violence. For all classes, the psychological loss is small and short-lived for being fired, death of close friend, death of a relative, serious illness of a relative, and being a victim of property crime. This latter set of results suggests that our model is not failing to capture important confounders that would have driven large psychological effects for all event types.

Figure 5 further demonstrates the extent of heterogeneity in the total psychological loss (TPL) associated with a standardised event (SE); see equation (13) in Section 2. Approximately 10 percent of the sample is estimated to experience a loss totalled across all periods of only around 0.05 units of standardised psychological health (corresponding to 5 percent of a standard deviation). Approximately 6 percent of the sample is estimated to experience a loss of around 0.25 units (25 percent of a standard deviation). The dynamic finite mixture model thus predicts substantive differences between the most resilient and least resilient individuals in our sample. Figure 6 further presents the total psychological loss associated with each event separately, similarly demonstrating the significant level of heterogeneity across individuals, but also highlighting considerable variation across the different types of adverse events.

4.3. Resilience versus the severity of major life events

While the HILDA survey asks respondents about major life events they experienced in the last 12 months it does not directly ask about the severity of those events. In any case, using such ex-post assessments would be problematic, because they could themselves be a function of an individual's resilience. To address this issue, we provide evidence in support of our resilience interpretation for the two economic events: major financial worsening, and fired or made redundant.

In terms of a major financial worsening we examine the size of the change in household income associated with this event, separately by whether the individual is above or below the median of our resilience measure (TPL). To do this we estimate fixed effects regressions of the log of household income on whether they experienced a major financial worsening, together with year fixed-effects and a polynomial of age. Importantly, we find an almost identical estimated decrease in income for high and low resilience groups: for the high resilience group, a major financial worsening is associated with a -0.096 (*t*-stat = -4.52) decline in log household income, and for the low resilience group the estimate is -0.097 (t-stat = -7.11). This suggests that the least resilient did not experience a more severe financial event than the resilient.

For being fired or made redundant, we use the individuals reported pre-event expectation that they will lose their job in the next 12 months (given as a percentage chance). If resilient people are able to avoid future events, rather than being better able to cope with events (our baseline interpretation), then we should find that resilient people are less likely to believe they will lose their job. In contrast, we find that resilience (TPL) is not a significant predictor of higher job loss expectations: a one-standard deviation increase in TPL is estimated to decrease the expected chance of losing your job by only 0.24% (*t*-stat = -0.17). So, on this measure, shock intensity is the same between the least and most resilient.

To further examine our interpretation that resilience measures quick bounce-back from negative shocks, rather than shock attributes, we look at whether the resilient are more confident that they will bounce back when it comes to jobs. We regress the percentage chance an individual thinks that they will find and accept a job at least as good in terms of wages and benefits as their current job (in the next 12 months). This is found to be significantly related to our resilience measure (coefficient = -7.181; *t*-stat = -2.10). So, those with high resilience are no more likely to expect to lose their job in the next 12 months, but are more likely to think that they can get a better job. The latter result is consistent with being resilient.

4.4. Relationship between psychological resilience and clinical measures of mental health

Table 3 shows the relationship between TPL following a SE and three clinically-related measures of mental health available in the HILDA data. Here we have split the distribution of TPL into terciles, with Tercile 1 being the most resilient individuals, and Tercile 3 being the least resilient. The differences are substantive with individuals in Tercile 3 having around a 5 times higher likelihood of currently being diagnosed with depression and/or anxiety, currently taking prescription medication for depression and/or anxiety, and having seen a psychiatrist or psychologist in the past year, respectively, than the most resilient (Tercile 1). Notably, these very strong correlations remain after controlling for demographic characteristics, such as age, gender and educational attainment.

4.5. The predictive validity of the resilience measure

We examine the predictive validity of our resilience (TPL) measure by testing if it predicts the psychological responses of out-of-sample life events. In particular, we use waves 13-17 as our hold-out sample, and re-estimate individual resilience with the measurement model described in Section 2 using only waves 1-12. Importantly, we find that our measure of resilience based on using the waves 1-12 explains 94% of the variation in predicted TPL using the waves 1-17 sample.[21]

We estimate a number of individual-level fixed-effects regression models using resilience measured from waves 1-12, applied to life events and variation in psychological health in the wave 13-17 hold-out sample. We also test whether our resilience measure is protective in terms of more clinical mental health outcomes. In addition to the life event and resilience interaction terms, we include a set of time-varying covariates and year fixed-effects.

We find that for those experiencing a major life event in the past 12 months (waves 13-17), having a one-standard deviation higher resilience (TPL) significantly reduces (protects or insures against) the impact on psychological health by 0.274 units (se=0.093).[22] Similarly, it reduces: (i) the probability of currently being diagnosed with depression and/or anxiety by 3 percentage points (0.030, se=0.003); (ii) the probability of currently taking prescription medication for depression and/or anxiety by 2.1 percentage points (0.021, se=0.002); and (iii) the probability of having seen a psychiatrist or psychologist in the past year by 1.8 percentage points (0.018, se=0.002). Overall, these results provide additional support for the usefulness of our resilience measure.

[21] Table A3 shows that the class membership probabilities estimated using the waves 1-12 are very correlated with those obtained from the waves 1-17 sample.

[22] If we use estimated membership probability of the most resilience class (Class 1) rather than TPL, we also find a significant protective effect: coefficient on the interaction equals 0.982 (se=0.306). Corresponding estimates for the three clinical measures are 0.082 (se=0.009), 0.068 (se=0.007) and 0.060 (se=0.007), respectively, i.e. minus 8.2, 6.8 and 6.0 percentage points. The full set of results are presented in Appendix Tables A4 and A5.

4.6. Resilience, gender, age, education, cognitive ability, Big-5 personality and locus of control

Finally, in Table 4 we show how strongly our measure of resilience is related to gender, age, educational attainment, cognitive ability, Big-5 personality traits and locus of control (see Appendix C for details of these covariates).[23] Again, our measure of resilience is a person's TPL, which we have standardised to have mean zero and standard deviation one, with a higher value therefore meaning less resilient. We estimate an OLS regression, as well as quantile regressions to explore the strength of the associations at different points of the resilience distribution.

We find that males are more resilient (-0.240 of a standard deviation), thus having a significantly lower TPL than females following adverse life events, and this gender difference is found across the whole TPL distribution. Neither the OLS or quantile regressions show any evidence of significant age differences in TPL, and importantly there is little evidence that educational attainment is linked with resilience. If anything, the results suggest that a university degree is associated with lower resilience (higher TPL) at the very bottom (10%) of the distribution. Studies in the psychology literature have identified high intelligence as being predictive of resilience in the face of adversity (e.g. Martinez-Torteya et al., 2009). Consistent with this literature, we find that cognitive ability is positively and significantly associated with our measure of resilience (-0.064), and, as with gender, this strong association is found across the TPL distribution (with perhaps the exception of the 90% quantile). We find that four of the Big-5 personality traits are significantly related to TPL in intuitive directions, with agreeableness being the exception. In particular, we find that emotional stability is most strongly related to TPL, with a one standard deviation increase associated with a -0.126 standard deviation lower TPL following major life events, and this relationship is strongly found across all but the highest resilience level (90^{th} decile). In contrast, openness is positively related to TPL, with the relationship being strongest above the median in the distribution.

A number of recent economic studies have found that having an external LOC (or low self-efficacy) is associated with lower human capital and poorer economic outcomes (see, for example, Cebi, 2007; Caliendo et al., 2015; McGee, 2015; Cobb-Clark et al., 2016; Schurer, 2017; Lekfuangfu et al., 2018; Cobb-Clark et al., 2020).[24] With regards to psychological resilience, Buddelmeyer and

---

[23] In a similar exercise Becker et al. (2012) examine the strength of the relationship between economic preferences (time and risk) and personality (Big-5) and find only low correlations, suggesting that they are complements and cannot be used as substitutes.

[24] A number of papers have used German panel data (GSOEP) to establish the links between LOC and economic and health outcomes. For example, Caliendo et al. (2015) find evidence that individuals with an internal LOC undertake more job search. Schurer (2017) finds that high internal LOC predicts men's ability to remain in the labour force following a health shock. Caliendo et al. (2020) find that higher internal LOC results in increased take-up of general training. Using Australian panel data (HILDA) Cobb-Clark et al. (2014) find that individuals with an internal LOC are more likely to eat well and exercise regularly, and Cobb-Clark et al. (2016) show that households with an internal LOC tend to save more. Other papers have looked at the stability of LOC in adulthood (Cobb-Clark and Schurer, 2012), and how LOC evolves in early life (Elkins and Schurer, 2020).

Powdthavee (2016) find that having an internal LOC has a significant protective effect on mental health for males (but not females) after experiencing bereavement, a major worsening of finances, and serious personal injury or illness.

Given this literature on LOC it is interesting to establish how strongly our ‘revealed’ measure of resilience is associated with the ‘stated’ LOC measure.[25] We find that an external locus of control is strongly and significantly related to having higher psychological loss (TPL) following adverse events, and this is evident across the entire TPL distribution. In fact, locus of control has the strongest relationship with our resilience measure, with a one standard deviation increase in external locus of control being roughly equal in magnitude to the estimated gender gap in resilience.

5. Conclusion

A key focus of many Governments is to strengthen the resilience of their people, communities and businesses in the face of adverse events. In this paper we have provided new evidence on the distribution of psychological resilience using 17 waves of panel data, examining how individuals respond to ten major life events, spanning a major worsening of finances, the death of a spouse, and being a victim of violent crime. We answer the call by leading economists and psychologists to provide such evidence (Clark, 2016; Kalisch et al., 2017), and the COVID-19 crisis that has further raised the importance of increasing resilience (Habersaat et al., 2020).

Although there is some debate in psychology about whether resilience is a fixed trait or a dynamic process, to gain tractability we have assumed the former. The fixed trait will be partly genetic (e.g. Amstadter et al., 2014), and partly the result of early life investments leading to skills that are stable in adulthood (Cunha and Heckman, 2009; Schurer, 2017). The findings of Cobb-Clark and Schurer (2012, 2013) indicate there is a high level of stability in personality traits and locus of control for adults aged 25 to 60 years. In particular, they find that, “Intra-individual changes are generally unrelated to adverse life events and are not economically meaningful.”

We have applied a dynamic finite mixture methodology to measure resilience that we believe tackles many of the empirical challenges, and enables us to establish the extent of heterogeneity in the population, using the best available panel data to do so. The model allows for individual heterogeneity in anticipation, contemporaneous responses, and adaptation profiles, to ten major adverse life events. Thus, our measure of resilience is ‘revealed’ by the actual psychological

[25] An example of questions asked in HILDA used to form a locus of control measure are: on a 0-7 scale reflecting the strength to which indviduals agree with the statements, "I have little control over the things that happen to me", "There is really no way I can solve some of problems I have", "There is little I can do to change many of the important things in my life", "I often feel helpless in dealing with the problems of life", "Sometimes I feel that I'm being pushed around in life", "What happens to me in the future mostly does not depend on me", and "I cannot do just about anything I really set my mind to do" (Cobb-Clark et al., 2014).

responses of individuals in contrast to 'stated' measures of resilience, where an individual is asked questions about how well they respond to life's difficulties (and an index is created). Importantly, we control for the initial conditions problem, and selection on fixed unobservable characteristics, because individuals do not randomly experience life events. We find that around 34% of individuals experience the largest psychological losses from major life events (i.e. the least resilient), with generally substantial differences between the most and least resilient individuals in both the immediate response to events and in the speed of adaptation. This is especially the case for death of a spouse and a major worsening of financial situation, which are the 'worst' events in terms of total psychological loss. We also find that males have a lower psychological response to adverse life events, and that cognitive ability may be a protective factor for psychological loss; which is evident across the whole of the resilience distribition. In contrast, we find no evidence that resilience changes with age.

We find support for our measure of resilience in the strength of its relationship with diagnosed mental health conditions. In particular, the least resilient are seven times more likely to be currently diagnosed with depression or anxiety than those estimated to be the most resilient. We also find that our measure strongly predicts the psychological response to an out-of-sample major economic event. Further, we show that our resilience measure captures a different construct to locus of control, and the Big-5 personality traits, but that it is correlated with these traits in plausible directions. Importantly, we find that locus of control is strongly correlated with our measure across the whole of the resilience distribution. This result provides support for investing in non-cognitive skills that reduce the psychological damage-function from major adverse life events.

Empirically modelling resilience based on responses to life events (revealed resilience), compared to directly asking individuals how resilient they believe that they are (stated-resilience), is complex with detailed longitudinal data required, and while we have had to make modelling assumptions, we believe that our approach advances the literature. Although all captured in our flexible resilience profiles, a limitation of our study is that we are not able to distinguish between resilience that arises from a dampened response to life events, compared to resilience due to behaviour that actively finds ways to tackle adversity. However, we have shown that our resilience measure is strongly correlated with locus of control.

We have also been able to provide some evidence that our resilience measure is not capturing differences in the severity of life events. The observed income decrease associated with a negative financial event did not differ between those with high and low levels of resilience. We also found that those with high and low resilience had similar expectations of job loss, prior to losing their job. We also found evidence that highly resilient people thought it more likely that they would be able to find an equivalently good job if they lost their current one, which is what we would expect if resilience picks up the ability to bounce back from negative events, rather than the severity of those events themselves.

Finally, the large number of identifying major life events and the general robustness of the resilience measure makes it unlikely that our results depend on functional form or the omission of any other life events. Plus, the fact that we are not finding large impacts for many of the life events, including being fired, death or illness of a relative, death of a friend, and being a victim of property crime, suggests that we are not failing to account for important confounders. Future research might additionally look for heterogeneity in the very tails of the resilience distribution, because public costs in crime and health, for example, are often related to behavioural extremes.

References

Amstadter, AB., Myers, JM. And Kendler, KS. (2014). Psychiatric resilience: Longitudinal twin study. *British Journal of Psychiatry*, 205, pp. 275-280.

Arouri, M., Nguyen. C. and Youssef, AB. (2015). Natural disasters, household welfare, and resilience: Evidence from rural Vietnam. *World Development*, 70, pp. 59-77.

Asheim, GB., Bossert, W. D'Ambrosio, C. and V¨ogele, C. (2019). The measurement of resilience. ECINEQ Working Paper 2019-486.

Bacci, S., Bartolucci, F., Bettin, G. and Pigini, C. (2019). A panel class growth model for migrant's remittances: An application to the German Socio-Economic Panel. *Journal of the Royal Statistical Society, Series A*, 182, PP. 1607-1632.

Baron, E., Bass, J., Murray, SM., Schneider, M. and Lund, C. (2017). A systematic review of growth curve mixture modelling literature investigating trajectories of perinatal depressive symptoms and associated risk factors. *Journal of Affective Disorder*, 233, pp. 194-208.

Baudry, J-P. (2015), Estimation and model selection for model-based clustering with the conditional classification likelihood, *Electronic Journal of Statistics*, 9, pp. 1041-1077.

Becker, A., Deckers, T., Dohmen, T., Falk, A. and Kosse, F. (2012). The relationship between economic preferences and psychological personality measures. *Annual Review of Economics*, 4, pp. 453-478.

Biernacki, C., Celeux, G., & Govaert, G. (2000). Assessing a mixture model for clustering with the integrated completed likelihood. *IEEE transactions on pattern analysis and machine intelligence*, *22*(7), 719-725.

Bonanno, GA. (2004). Loss, trauma, and human resilience: Have we underestimated the human capacity to thrive after extremely adverse events? *American Psychologist*, 59, pp. 20-28.

Bonanno, GA., Galea, S., Bucciarelli, A. and Viahov, D. (2006). Psychological resilience after disaster: New York City in the aftermath of the September 11th terrorist attack. *Psychological Science*, 17, pp. 181-186.

Bonanno, GA., Galea, S., Bucciarelli, A. and Viahov, D. (2007). What predicts psychological resilience after disaster? The role of demographics, resources, and life stress. *Journal of Consulting and Clinical Psychology*, 75, pp. 671-682.

Bonanno, GA., Brewin, CR., Kaniasty, K. and La Greca, AM. (2010). Weighing the costs of disaster: Consequences, risks, and resilience in individuals, families, and communities. *Psychological Science in the Public Interest*, 11, pp. 1-49.

Bonanno, GA. (2012). Uses and abuses of the resilience construct: Loss, trauma, and health-related adversities. *Social Science and Medicine*, 74, pp. 753-756.

Bonanno, GA., Kennedy, P., Galatzer-Levy, IR., Lude, P. and Elfström, ML. (2012). Trajectories of resilience, depression, and anxiety following spinal cord injury. *Rehabilitation Psychology*, 57, pp. 236-247.

Bonanno, GA., Romero, SA. and Klein, S. (2015). The temporal elements of psychological resilience: An integrative framework for the study of individuals, families, and communities. *Psychological Inquiry*, 26, pp. 139-169.

Bonhomme, S. and Robin, JM. (2009). Assessing the equalizing force of mobility using short panels: France, 1990–2000. *The Review of Economic Studies*, 76, pp. 63-92.

Borghans, L., Golsteyn, BH., Heckman, J. and Humphries, JE. (2011). Identification problems in personality psychology. *Personality and individual differences*, 51, pp. 315-320.

Brown, S., Durand, RB., Harris, MN. and Weterings, T. (2014). Modelling financial satisfaction across life stages: A latent class approach. *Journal of Economic Psychology*, 45, pp. 117-127.

Bruhin, A., Fehr-Duda, H., and Epper, T. (2010). Risk and rationality: Uncovering heterogeneity in probability distortion. *Econometrica*, 78, pp. 1375-1412.

Bruhin, A., Fehr, E., and Schunk, D. (2019). The many faces of human sociality: Uncovering the distribution and stability of social preferences. *Journal of the European Economic Association*, 17, pp. 1025-1069.

Buddelmeyer, H. and Powdthavee, N. (2016). Can having internal locus of control insure against negative shocks? Psychological evidence from panel data. *Journal of Economic Behavior and Organization*, 122, pp. 88-109.

Caliendo, M., Cobb-Clark, DA. And Uhlendorff, A. (2015). Locus of control and job search strategies. *Review of Economics and Statistics*, 97, pp. 88-103.

Carrieri, V., Davillas, A. and Jones, AM. (2020). A latent class approach to inequity in health using biomarker data. *Health Economics*, *forthcoming.*

Cebi, M. (2007). Locus of control and human capital investment revisited. *Journal of Human Resources*, XLII, pp. 919-932.

Chen, J., Li, P. and Fu, Y. (2012). Inference on the order of a normal mixture. *Journal of the American Statistical Association*, 107, pp. 1096-1105.

Clark, AE., Etilé, F., Postel-Vinay, F., Senik, C. and van der Straeten, K. (2005). Heterogeneity in reported well-being: Evidence from twelve European countries. *Economic* Journal, 115, pp. C118-C132.

Clark, AE., Diener, E., Georgellis, Y. and Lucas, RE. (2008). Lags and leads in life satisfaction: A test of the baseline hypothesis. *Economic Journal*, 118, pp. F222-F243.

Clark, AE. (2016). Adaptation and the Easterlin Paradox. In *Advances in Happiness Research: A Comparative Perspective*, by T. Tachibanaki (ed.), Chapter 6, Springer.

Cobb-Clark, DA. and Schurer, S. (2012). The stability of big-five personality traits. *Economics Letters*, 115, pp. 11-15.

Cobb-Clark, DA. and Schurer, S. (2013). Two economists' musings on the stability of Locus of Control. *Economic Journal*, 123, pp. F358-F400.

Cobb-Clark, DA., Kassenboehmer, SC. and Schurer, S. (2014). Healthy habits: The connection between diet, exercise, and locus of control. *Journal of Economic Behavior and Organization*, 98, pp. 1-28.

Cobb-Clark, D., Kassenboehmer, S. and Sinning, M. (2016). Locus of control and savings. *Journal of Banking and Finance*, 73, pp. 113-130.

Cobb-Clark, DA., Caliendo, M., Obst, C., Seitz, H. and Uhlendorff, A. (2020). Locus of control and investments in training. *Journal of Human Resources*, forthcoming.

Connor, KM. and Davidson. JRT. (2003). Development of a new resilience scale: The Connor-Davidson Resilience Scale (CD-RISC). *Depression and Anxiety*, 18, pp. 76-82.

Conte, A., Hey, J. D., and Moffatt, P. G. (2011). Mixture models of choice under risk. *Journal of Econometrics*, 162, pp. 79-88.

Cuaresma, JC., Grun, B., Hofmarcher, P., Humer, S. and Moser, M. (2016). Unveiling covariate inclusion structures in economic growth regression using latent class analysis. *European Economic Review*, 81, pp. 189-202.

Cunha, F., Heckman, JJ. and Schennach, SM. (2010). Estimating the technology of cognitive and noncognitibve skill formation. *Econometrica*, 78, pp. 883-931.

Cunha, F. and Heckman, JJ. (2009). The economics and psychology of inequality and human development. *Journal of the European Economic Association*, 7, pp. 320-364.

Cutter, SL., Ahearn, JA., Amadei, B., Crawford, P. et al. (2013). Disaster resilience: A national imperative. *Environment: Science and Policy for Sustainable development*, 55, pp. 25-29.

Deb, P. and Trivedi, P.K. (2002) The structure of demand for health care: latent class versus two-part models. *Journal of Health Economics*, 21, pp. 601-625.

Dempster, AP. and Laird, NM. (1977). Maximum likelihood from incomplete data via the EM algorithm. *Journal of the Royal Statistical Society*, 39, pp. 1-38.

Diener, E., Suh, EM., Lucas, RE. and Smith, HL. (1999). Subjective well-being: Three decades of progress. *Psychological Bulletin*, 125, pp. 276-302.

Diener, E., Lucas, RE. and Scollon, CN. (2006b). Beyond the hedonic treadmill: Revising the adaptation theory of well-being. *American Psychologist,* 61, pp. 305–314.

Eckardt, M., Brettschneider, C., van den Bussche, H. and Konig, HH. (2016). Analysis of health care costs in elderly patients with multiple chronic conditions using a finite mixture of generalized linear models. *Health Economics*, 26, pp. 582-599.

Elkins, R. and Schurer, S. (2020). Exploring the role of fathers in non-cognitive skill development over the lifecourse. *Journal of Population Economics* 33, pp. 957-1004.

Etilé, F. (2006). Who does the hat fit? Teenager heterogeneity and the effectiveness of information policies in preventing cannabis use and heavy drinking. *Health Economics*, 15, pp. 697-718.

Etilé, F. and Sharma, A. (2015). Do high consumers of sugar-sweetened beverages respond differently to price changes? A Finite Mixture IV-Tobit approach. *Health Economics*, 24, pp. 1147-1163.

Fletcher, D. and Sarkar, M. (2013). Psychological resilience: A review and critique of definitions, concepts and theory. *European Psychologist*, 18, pp. 12-23.

Frijters, P., Johnston, D. and Shields, MA. (2011). Life satisfaction dynamics with quarterly life event data. *Scandinavian Journal of Economics*, 113, pp. 190-211.

Galatzer-Levy, IR., Bonanno, GA. and Mancini, AD. (2010). From marienthal to latent growth mixture modeling: A return to the exploration of individual differences in response to unemployment. *Journal of Neuroscience, Psychology and Economics*, 3, pp. 116-125.

Galatzer-Levy, IR. and Bonanno, GA. (2012). Beyond normality in the study of bereavement: Heterogeneity in depression outcomes following loss in older adults. *Social Science & Medicine*, 74, pp. 1987-1994.

Habersaat, KB., Betsch, C. et al. (2020). Ten considerations for effectively managing the COVID-19 transition. *Nature Human Behaviour*, 24th June.
Hanushek, E. A. (1974). Efficient estimators for regressing regression coefficients. *The American Statistician*, 28, pp. 66-67.
Hogg, D., Kingham, S., Wilson, TM. and Ardagh, M. (2016). The effects of relocation and level of affectedness on mood and anxiety symptom treatments after the 2011 Christchurch earthquake. *Social Science and Medicine*, 152, pp. 18-26.
Kalisch, R. et al. (2017). The resilience framework as a strategy to combat stress-related disorders. *Nature Human Behaviour*, November, pp. 784-790.
Kariuki, M., Honey, A., Emerson, E., Llewellyn, G. (2011). Mental health trajectories of young people after disability onset. *Disability and Health Journal*, 4, pp. 91-101.
Kasahara, H. and Shimotsu, K. (2009). Nonparametric identification of finite mixture models of dynamic discrete choices. *Econometrica, 77*, pp. 135-175.
Kettlewell, N., Morris, RW., Ho, N., Cobb-Clark, DA., Cripps, S. and Glozier, N. (2020). The differential impact on major life events on cognition and affective wellbeing. *SSM - Population Health*, forthcoming.
Lee, J., Blackmon, BJ., Cochran, DM., Kar, B. and Stubbs Gunnell, M. (2018). Community resilience, psychological resilience, and depressive symptoms: An examination of the Mississippi Gulf Coast 10 years after Hurricane Katrina and 5 years after the Deepwater Horizon oil spill. *Disaster Medicine and Public Health Preparedness*, 12, pp. 241-248.
Lekfuangfu, WN., Powdthavee, N., Warrinnier, N. and Cornaglia, F. (2018). Locus of control and its intergenerational implications for early childhood skill formation. *Economic Journal*, 128, pp. 298-329.
Lindsay, B. G. (1983). The geometry of mixture likelihoods, part II: the exponential family. *The Annals of Statistics*, 11, pp. 783-792.
Liu, X., & Shao, Y. (2003). Asymptotics for likelihood ratio tests under loss of identifiability. *The Annals of Statistics*, 31, pp. 807-832.
Longstaff, PH., Armstrong, NJ., Perrin, K., Parker, WM. and Hidek, MA. (2010). Building resilient communities: A preliminary framework for assessment. *Homeland Security Affairs*, 6.3, September.
Lucas, RE., Clark, AE., Georgellis, Y. and Diener, E. (2004). Unemployment alters the set point for life satisfaction. *Psychological Science,* 15, pp. 8-13.
Lucas, RE. (2005). Time does not health all wounds: A longitudinal study of reaction and adaptation to divorce. *Psychological Science*, 16, pp. 945-950.
McGee, A. (2015). How the perception of control influences unemployed job search. *Industrial Labor Relations Review*, 68, pp. 184-211.
Mancini, AD., Bonanno, GA. and Clark, AE. (2011). Stepping off the hedonic treadmill: Latent class analyses of individual differences in response to major life events. *Journal of Individual Differences*, 32, pp. 144-152.
Martinez-Torteya, C., Bogat, GA., von Ete, A., and Levendosky, AA. (2009). Resilience among children exposed to domestic violence: The role of risk and protective factors. *Child Development*, 80, pp. 562-577.
McGiffin, JN., Galatzer-Levy, IR. and Bonanno, GA. (2019). Socioeconomic resources predict trajectories of depression and resilience following disability. *Rehabilitation Psychology*, 64, pp. 98-103.
McLachlan, G., & Peel, D. (2000). *Finite Mixture Models*. London: John Wiley & Sons.
Norris, FH. and Stevens, SP. (2007). Community resilience and the principles of mass trauma intervention. *Psychiatry*, 70, pp. 320-328.
Norris, FH., Tracy, M. and Galea, S. (2009). Looking for resilience: Understanding the longitudinal trajectories of responses to stress. *Social Science and Medicine*, 68, pp. 2190-2198.
Oswald, AJ. and Powdthavee, N. (2008). Does happiness adapt? A longitudinal study of disability with implications for economists and judges. *Journal of Public Economics*, 92, pp. 1061-1077.
Phelps, AJ., Steel, Z., Metcalf, O. and Alkemade, N. et al. (2018). Key patterns and predictors of response to treatment for military veterans with post-traumatic stress disoder: A growth mixture modelling approach. *Psychological Medicine*, 48, pp. 95-103.
Phillips, SP., Auais, M., Belanger, E., Alvarado, B and Zunzunegui, MV. (2016). Life-course social and economic circumstances, gender, and resilience in older adults: The longitudinal International Mobility in Aging Study (IMIAS). *SSM - Population Health*, 2, pp. 708-717.
Portnoy, GA., Relyea, MR., Decker, S., Shamaskin-Garroway, A., Driscoll, M., Brandt, CA. and Haskell, SG. (2018). Understanding gender differences in resilience among veterans: Trauma history and social ecology/ *Journal of Traumatic Stress*, 31, pp. 845-855.

Public health England (2014). Local action on health inequalities: Building children and young people's resilience in schools. Health Equity Evidence Review 2, September, London.

Pudney, S. (2008). The dynamics of perception. Modelling subjective well-being in a short panel. *Journal of the Royal Statistical Society: Series A*, 171, pp. 21-40.

Rao, H. and Greve, HR. (2017). Disasters and community resilience: Spanish Flu and formation of retail cooperatives in Norway. *Academy of Management*, 61, pp. 5-25.

Reifels, L., Pietrantoni, L., Prati, G., Kim, Y., Dean. G. et al. (2013). Lessons learned about psychosocial responses to disaster and mass trauma: An international perspective. *Journal of Psychotraumatology*, 4, pp. 22897.

Rotter, J. B. (1966). Generalized expectancies for internal versus external control of reinforcement. *Psychological monographs: General and applied*, 80, pp. 1-28.

Saxonhouse, G. R. (1976). Estimated parameters as dependent variables. *The American Economic Review*, 66, pp. 178-183.

Schurer, S. (2017). Bouncing back from health shocks: Locus of control and labour supply. *Journal of Economic Behavior and Organization*, 133, pp. 1-20.

Train, K. E. (2008). EM algorithms for nonparametric estimation of mixing distributions. *Journal of Choice Modelling*, 1, pp. 40-69.

Tsai, J., El-Gabalawy, R., Sledge, WH., Southwick, SM. and Pietrzak, RH. (2015). Post-traumatic growth among veterans in the USA: Results from the National Health and Resilience in Veterans Study. *Psychological Medicine*, 45, pp. 15-179.

Ware, JE. (2000). SF-36 Health Survey update. *Spine*, 25, pp. 3130-39.

White, H. (1980). A Heteroskedasticity-Consistent Covariance Matrix Estimator and a Direct Test for Heteroskedasticity, *Econometrica*, 48, pp. 817–838.

Wedel, M., DeSarbo W.S., Bult J.R. and Ramaswamy, V. (1993). A Latent Class Poisson Regression Model for Heterogeneous Count Data. *Journal of Applied Econometrics*, 8, pp. 397-411.

Zhu, Z., Galatzer, IR. And Bonanno, GA. (2014). Heterogeneous depression responses to chronic pain onset among middle-aged adults: A prospective study. *Psychiatry Research*, 217, pp. 60-66.

Figure 1: Empirical Distribution of Psychological Health

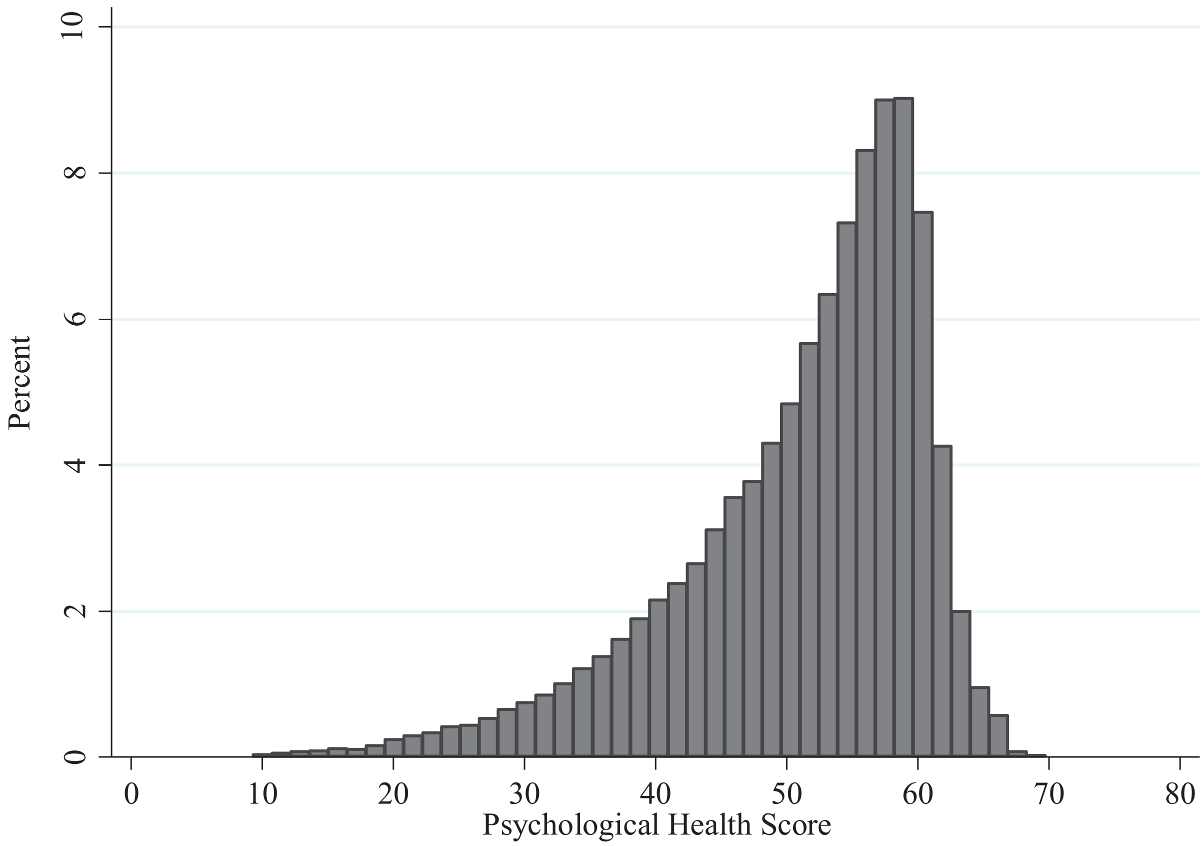
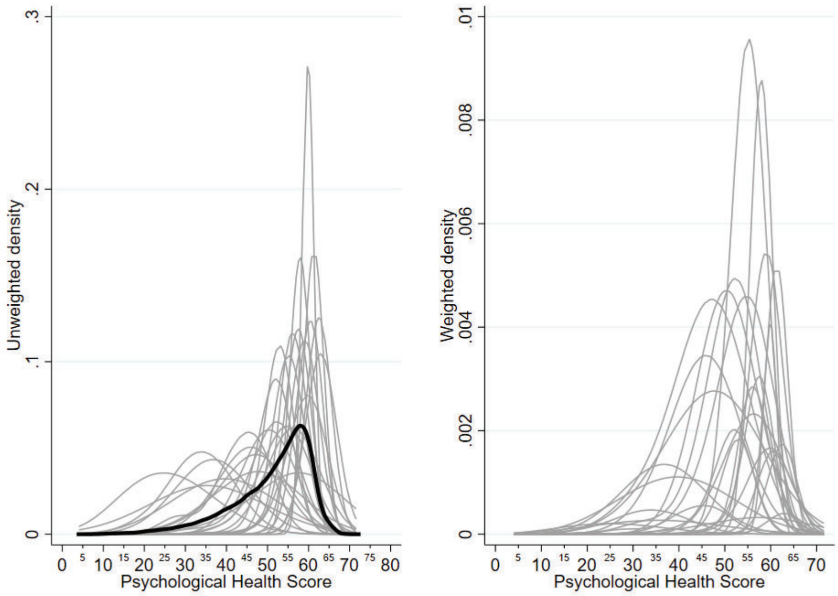
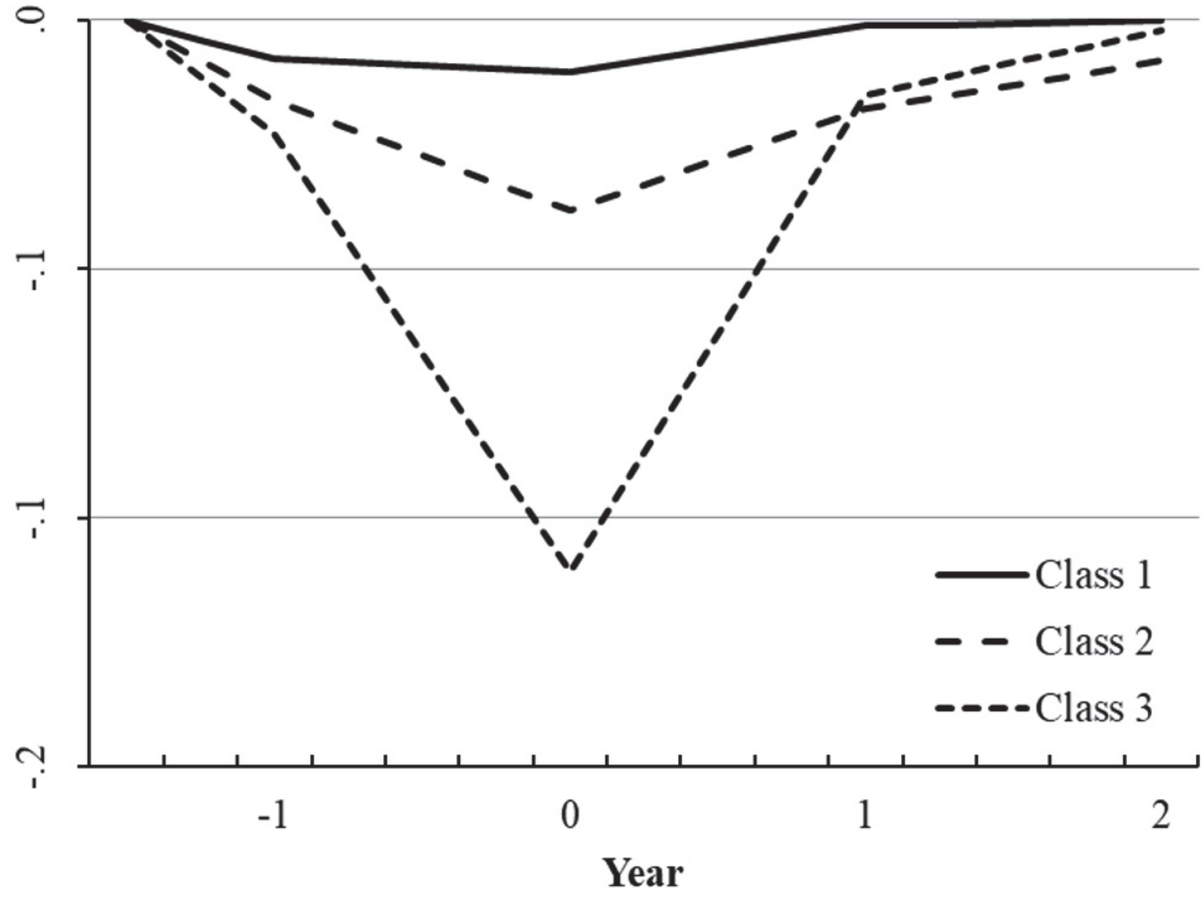


Figure 2: Empirical Density and Predicted Class Specific Densities



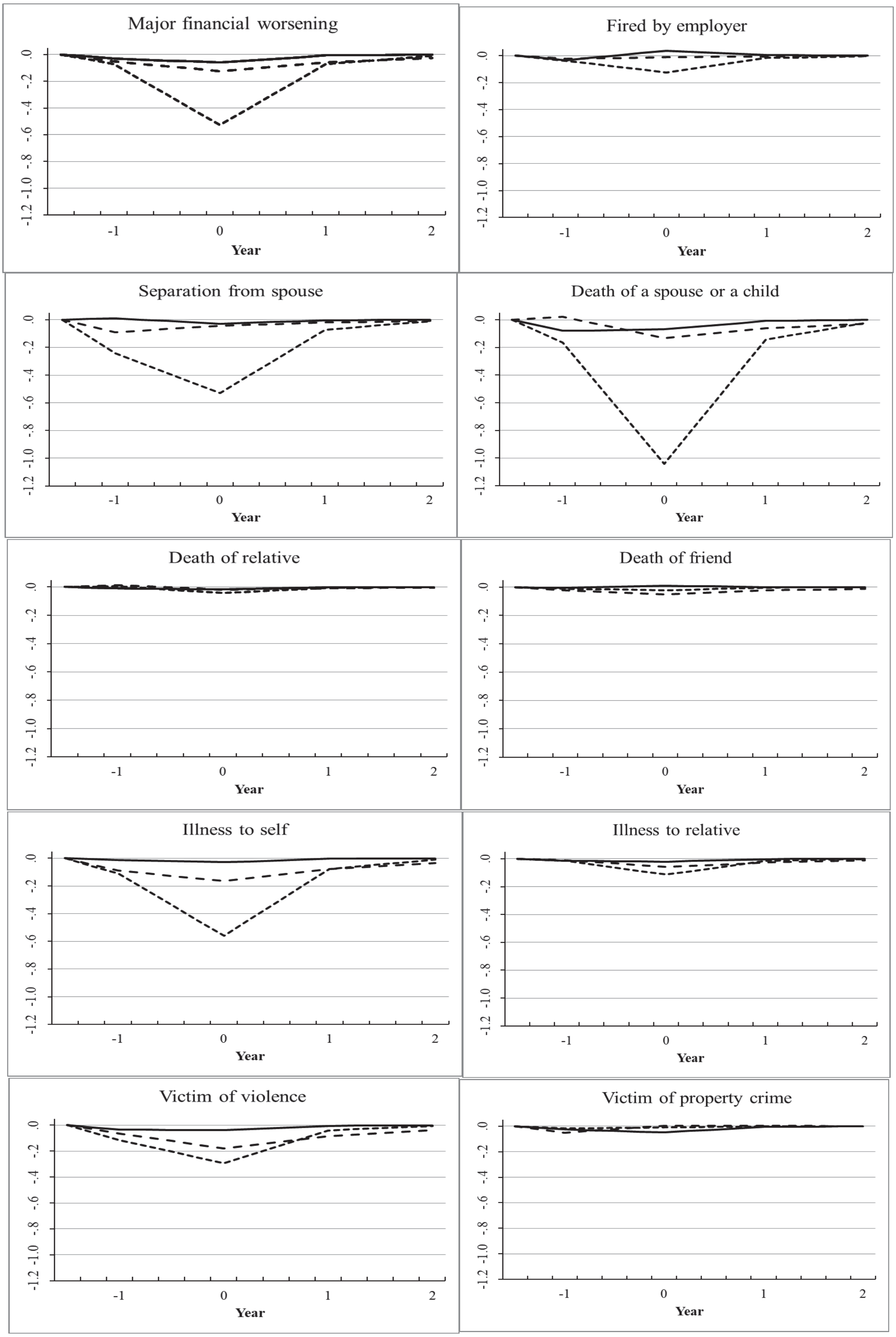
Notes: Black thick line: empirical distribution of psychological health (non-parametric fit); grey lines: unconditional class-specific distributions of psychological health simulated with the finite mixture dynamic model, weighted by the probabilities π_{kc} in the right panel, and unweighted in the left panel.

Figure 3: Heterogeneity in the Psychological Response Profiles to a Standardised Event (SE)



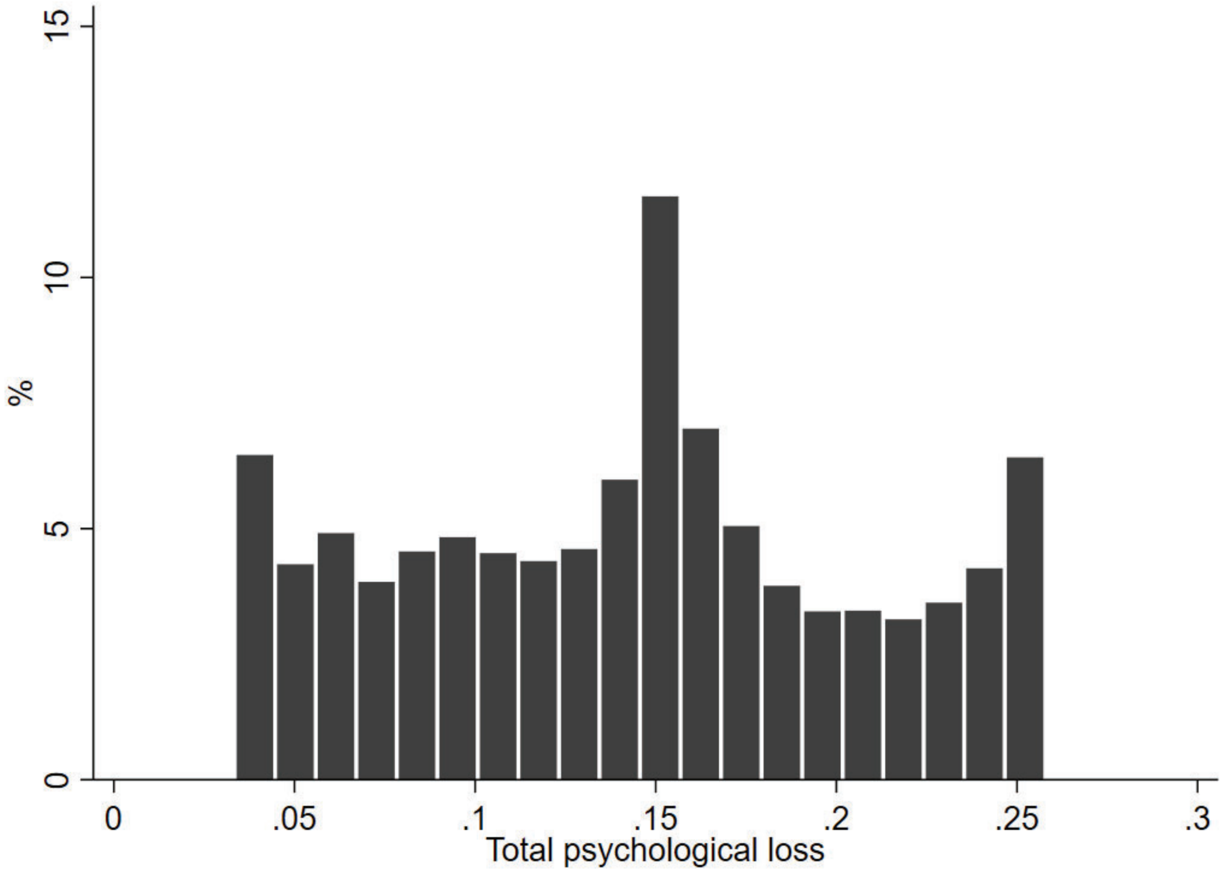
Notes: Y-axis represents the variation in psychological health in standard deviation units. X-axis represents time in years.

Figure 4: Heterogeneity in the Psychological Response Profiles by Major Life Event



Notes: Y-axis represents variation in mental health in standard deviation units. The solid, dash and dot profiles are generated by the parameter estimates shown in columns (2), (3) and (4) in Table 2, respectively.

Figure 5: Heterogeneity in the Total Pyschological Loss (TPL) to a Standardised Event (SE)



Notes: Histogram of the distribution of TPL from a Standardised Event (SE). The TPL is bounded above and below by values corresponding to the most and the less resilient class.

Figure 6: Heterogeneity in the Total Pyschological Loss by Major Life Event

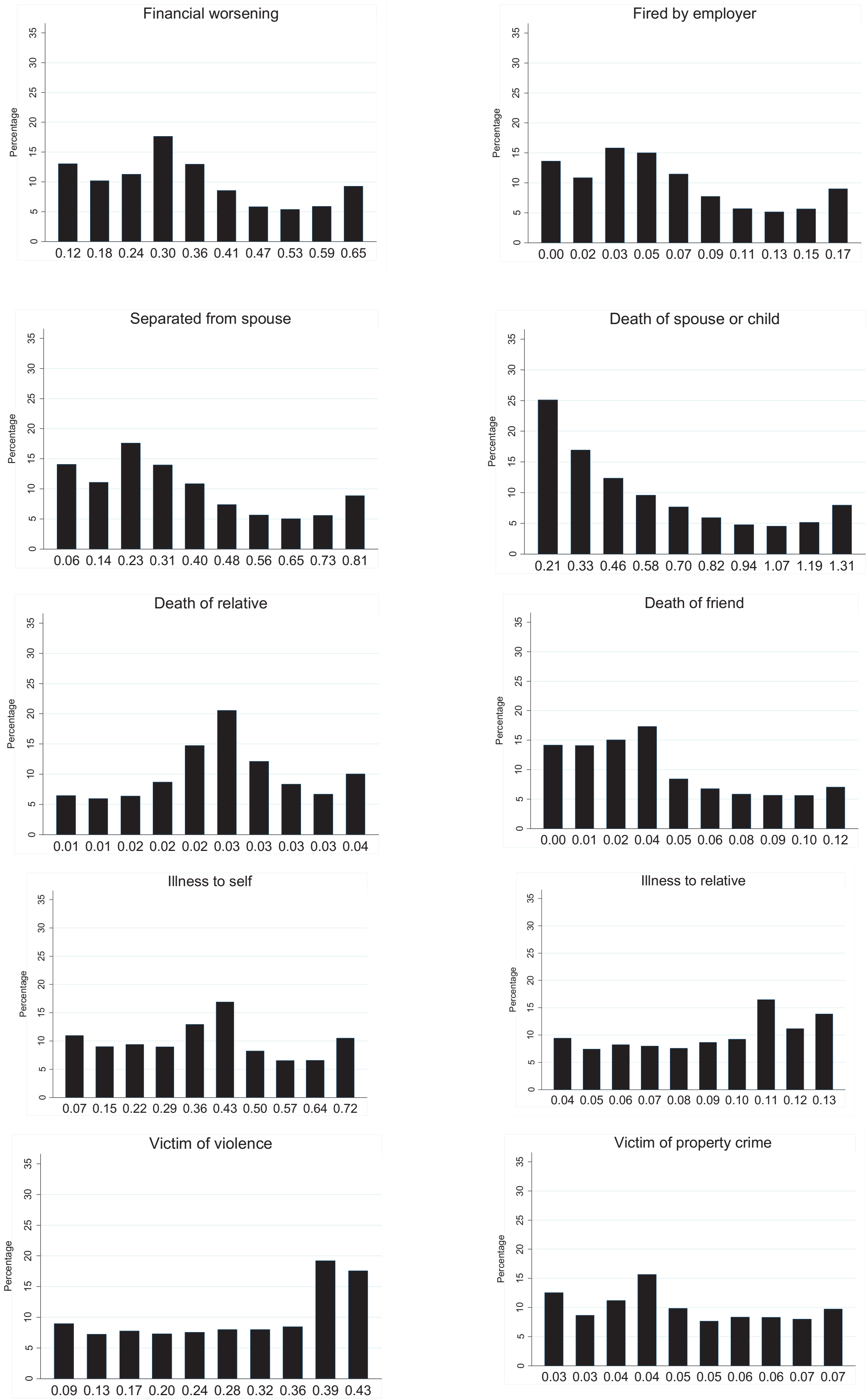


Table 1: Descriptive Statistics for Adulthood Variables

	Mean	Std. Dev.	Min	Max
Life Events				
Major worsening in financial situation	0.027	0.162	0	1
Fired or made redundant by an employer	0.026	0.160	0	1
Separated from spouse or long-term partner	0.023	0.151	0	1
Death of spouse or child	0.006	0.078	0	1
Death of other close relative / family member	0.112	0.316	0	1
Death of a close friend	0.110	0.313	0	1
Serious injury or illness to self	0.082	0.274	0	1
Serious injury or illness to a close relative	0.164	0.370	0	1
Victim of physical violence	0.008	0.091	0	1
Victim of a property crime	0.036	0.185	0	1
Contemporary characteristics				
Age	51.18	12.17	26	84
Male	0.469	0.499	0	1
Employed full-time	0.467	0.499	0	1
Employed part-time	0.211	0.408	0	1
Unemployed	0.017	0.131	0	1
Out of the labour force	0.304	0.460	0	1
Highest qualification: University degree	0.281	0.450	0	1
Highest qualification: Vocational diploma	0.330	0.470	0	1
Highest qualification: High school graduate	0.102	0.303	0	1
Highest qualification: High school dropout	0.287	0.452	0	1
Log household income	11.08	0.696	7.183	14.65
Married or cohabiting	0.777	0.416	0	1
Divorced or separated	0.079	0.270	0	1
Single and never married	0.144	0.351	0	1
Number of children	0.599	0.991	0	8
Cognitive ability and personality traits				
Cognitive test score (std)	0.031	0.915	-3.508	3.188
External locus of control (std)	-0.014	0.951	-1.423	3.870
Extraversion (std)	-0.043	1.007	-3.178	2.381
Agreeableness (std)	0.032	0.937	-4.661	1.711
Conscientiousness (std)	0.113	0.971	-3.965	1.860
Emotional stability (std)	0.040	0.975	-3.696	1.662
Openness (std)	0.028	0.960	-2.984	2.598
Clinical measures of psychological health				
Current diagnosed depression / anxiety	0.108	0.310	0	1
Take depression/anxiety prescription meds	0.053	0.224	0	1
Seen psychiatrist/psychologist in past year	0.058	0.234	0	1

Notes: Sample size equals: 6,294 individuals (69,460 individual-waves) for life events, contemporary characteristics, and cognitive ability and personality traits; and 5,721 individuals for clinical measure of psychological health. The cognitive ability and personality trait measures have been standardised to have a mean of zero and a standard deviation of one in the full HILDA sample.

Table 2: Dynamic Random Effects and Finite Mixture Dynamic Models of Psychological Health

		Dynamic RE model	**Finite Mixture Dynamic Model**		
			Finite Mixture Parameters		
			c=1	**c=2**	**c=3**
		Lagged Psychological Health Parameter (ρ_i)			
Psychological health in *t*-1		0.219***	0.115***	0.465***	0.136***
		(0.004)	(0.007)	(0.009)	(0.008)
		Immediate (μ_{0i}) and Anticipation (μ_{1i}) Parameters			
Major financial worsening	*t*	-2.780***	-0.528**	-0.942***	-4.910***
		(0.150)	(0.211)	(0.295)	(0.269)
	t+1	-0.749***	-0.288	-0.498*	-0.674**
		(0.152)	(0.181)	(0.303)	(0.285)
Fired or made redundant	*t*	-0.331**	0.377*	-0.004	-1.119***
		(0.150)	(0.193)	(0.244)	(0.278)
	t+1	-0.509***	-0.315*	-0.219	-0.362
		(0.150)	(0.180)	(0.241)	(0.326)
Separation from spouse	*t*	-2.150***	-0.288	-0.311	-4.766***
		(0.167)	(0.193)	(0.306)	(0.275)
	t+1	-1.417***	0.094	-0.860***	-2.288***
		(0.162)	(0.194)	(0.282)	(0.314)
Death of spouse or child	*t*	-2.678***	-0.552*	-1.282**	-9.687***
		(0.296)	(0.317)	(0.499)	(0.413)
	t+1	-1.229***	-0.756***	0.222	-1.574***
		(0.296)	(0.261)	(0.496)	(0.474)
Death of close relative	*t*	-0.391***	-0.149**	-0.192	-0.411**
		(0.073)	(0.075)	(0.125)	(0.165)
	t+1	-0.029	-0.097	0.122	0.053
		(0.073)	(0.077)	(0.132)	(0.168)
Death of close friend	*t*	-0.173**	0.086	-0.449***	-0.210
		(0.078)	(0.076)	(0.132)	(0.166)
	t+1	-0.093	-0.057	-0.202	-0.098
		(0.077)	(0.077)	(0.132)	(0.176)
Injury or illness to self	*t*	-2.412***	-0.254***	-1.167***	-5.161***
		(0.088)	(0.094)	(0.158)	(0.161)
	t+1	-0.851***	-0.110	-0.842***	-1.032***
		(0.087)	(0.094)	(0.159)	(0.175)
Injury or illness to relative	*t*	-0.704***	-0.179***	-0.496***	-1.051***
		(0.066)	(0.065)	(0.112)	(0.139)
	t+1	-0.210***	-0.125*	-0.103	-0.138
		(0.066)	(0.069)	(0.117)	(0.152)
Victim of physical violence	t	-1.995***	-0.319	-1.411***	-2.630***
		(0.266)	(0.299)	(0.482)	(0.512)
	t+1	-1.305***	-0.326	-0.603	-1.095*
		(0.272)	(0.297)	(0.518)	(0.611)
Victim of property crime	*t*	-0.294**	-0.428***	0.265	-0.069
		(0.126)	(0.124)	(0.229)	(0.291)
	t+1	-0.275**	-0.234*	-0.490**	-0.161
		(0.131)	(0.127)	(0.221)	(0.282)

		Intercept (δ_i) and Error Variance (σ_i) Parameters		
k=1, probability weight p_{1c}	-	5.5%	0.6%	2.2%
Intercept		32.181***	1.182	27.593***
		(0.748)	(1.053)	(0.826)
Variance		2.127***	7.425***	3.572***
		(0.058)	(0.622)	(0.172)
k=2, probability weight p_{2c}	-	9.2%	3.4%	7.3%
Intercept		30.648***	6.239***	30.038***
		(0.741)	(0.911)	(0.811)
Variance		3.413***	8.800***	5.152***
		(0.063)	(0.330)	(0.121)
k=3, probability weight p_{3c}	-	1.5%	1.7%	6.8%
Intercept		33.233***	9.942***	24.337***
		(0.754)	(0.786)	(0.814)
Variance		1.193***	2.499***	6.721***
		(0.043)	(0.144)	(0.202)
k=4, probability weight p_{3c}	-	4.8%	1.0%	7.6%
Intercept		33.171***	3.901***	26.928***
		(0.749)	(0.780)	(0.815)
Variance		3.094***	4.858***	9.452***
		(0.097)	(0.292)	(0.170)
k=5, probability weight p_{3c}	-	3.2%	7.6%	0.9%
Intercept		34.343***	10.132***	35.335***
		(0.754)	(0.768)	(0.910)
Variance		1.952***	3.986***	9.334***
		(0.057)	(0.141)	(0.333)
k=6, probability weight p_{3c}	-	0.4%	0.9%	2.1%
Intercept		39.789***	7.141***	34.108***
		(0.758)	(0.798)	(0.816)
Variance		3.220***	3.383***	3.882***
		(0.105)	(0.279)	(0.133)
k=7, probability weight p_{3c}		7.8%	9.8%	2.6%
Intercept		27.659***	8.173***	30.928***
		(0.748)	(0.748)	(0.827)
Variance		6.011***	5.657***	2.672***
		(0.132)	(0.148)	(0.104)
k=8, probability weight p_{3c}		1.4%	13.0%	1.0%
Intercept		36.350***	12.962***	16.864***
		(0.762)	(0.807)	(0.917)
Variance		2.592***	1.847***	13.100***
		(0.079)	(0.100)	(0.435)
k=9, probability weight p_{3c}		3.8%	2.4%	3.1%
Intercept		32.092***	11.454***	19.334***
		(0.762)	(0.789)	(0.854)
Variance		5.911***	1.927***	7.860***
		(0.164)	(0.072)	(0.239)

Notes: Column 1 reports results from a dynamic random effects model, where coefficients on lagged psychological health and life events are homogenous. Columns 2-4 report the estimated coefficients of the finite mixture dynamic model for classes 1 to 3 respectively. The upper panel of Table 2 reports the coefficients on lagged psychological health, and contemporaneous and future life events. The lower panel of Table 2 displays the finite mixture paramaters for intercept and variance heterogeneity. In both models, we include as additional control variables with homogenous effects (see Table A2): logarithm of household income, age, age squared, male, labour market status (full-time employment, part-time employment, unemployment, inactive (reference)), degree (university, vocationnal diploma, high-school, less than grade 12 (reference)), marital status (partnered, divorced or separated, single (reference)), number of children at home, year dummies. In both models, we also control for initial conditions by including the initial level of psychological health, as well as the individual average of all time-varying variables. Standard errors in parentheses. *, ** and *** denote statistical significance at the 0.10, 0.05 and 0.01 levels, respectively.

Table 3: Descriptive Statistics of Selected Adulthood Characteristics by Terciles of Total Psychological Loss (TPL) to a Standardised Event (SE)

	Terciles		
	1st	**2nd**	**3rd**
Clinical psychological health			
Current diagnosed depression / anxiety	4.6%	13.9%	24.2%
Take depression/anxiety prescription meds	2.6%	8.1%	14.8%
Seen psychiatrist/psychologist in past year	2.2%	5.8%	10.5%

Notes: Terciles of total psychological loss from a standardised event defined using the estimated 33rd and 66th centiles. Sample size equals 5,721 individuals for clinical outcomes.

Table 4: OLS and Quantile Regressions of Total Psychological Loss (TPL) Percentile on Demographic, Cognition, Big-5 Personality and Locus of Control

		Quantiles				
	OLS	**10th**	**25th**	**50th**	**75th**	**90th**
Male	-0.240***	-0.214***	-0.257***	-0.226***	-0.287***	-0.168***
	(0.026)	(0.024)	(0.036)	(0.030)	(0.043)	(0.035)
Age	-0.004	-0.011*	-0.017	-0.009	-0.006	0.013
	(0.008)	(0.007)	(0.011)	(0.009)	(0.013)	(0.012)
Age squared	-0.002	0.007	0.012	0.005	-0.001	-0.021
	(0.009)	(0.007)	(0.011)	(0.010)	(0.014)	(0.014)
University degree	0.005	0.073**	0.054	-0.023	-0.023	-0.053
	(0.036)	(0.032)	(0.047)	(0.043)	(0.061)	(0.039)
Other post-school qualification	0.010	-0.006	-0.008	0.002	0.067	0.022
	(0.032)	(0.030)	(0.046)	(0.036)	(0.050)	(0.041)
High school graduate	-0.050	-0.057*	-0.052	-0.069	-0.051	-0.056
	(0.043)	(0.032)	(0.060)	(0.047)	(0.072)	(0.041)
Cognitive test score	-0.064***	-0.065***	-0.085***	-0.072***	-0.066***	-0.028*
	(0.014)	(0.015)	(0.020)	(0.016)	(0.024)	(0.015)
Extraversion	-0.053***	-0.083***	-0.084***	-0.055***	-0.040*	0.004
	(0.013)	(0.013)	(0.017)	(0.015)	(0.021)	(0.011)
Agreeableness	0.006	-0.010	-0.016	0.010	0.039*	0.035*
	(0.014)	(0.014)	(0.020)	(0.015)	(0.023)	(0.018)
Conscientiousness	-0.034**	-0.024**	-0.050***	-0.042***	-0.046**	-0.011
	(0.013)	(0.011)	(0.018)	(0.015)	(0.022)	(0.013)
Emotional stability	-0.126***	-0.136***	-0.190***	-0.149***	-0.096***	-0.026*
	(0.014)	(0.018)	(0.019)	(0.015)	(0.022)	(0.014)
Openness	0.056***	-0.013	0.008	0.060***	0.140***	0.070***
	(0.014)	(0.011)	(0.019)	(0.016)	(0.023)	(0.016)
(External) locus of control index	0.205***	0.170***	0.263***	0.221***	0.212***	0.107***
	(0.014)	(0.019)	(0.019)	(0.015)	(0.022)	(0.013)
Sample size	6294	6294	6294	6294	6294	6294

Notes: Estimates from an OLS and a Quantile Regression on Total Psychological Loss (TPL), which for ease of interpretation has been standardised (mean zero, std deviation one). All indices used as regressors have also been standardized (0,1). Standard errors in parentheses. *, ** and *** denote statistical significance at the 0.10, 0.05 and 0.01 levels, respectively.

Appendix A: Additional Results

Table A1: Measurement of the Psychological (Mental) Health Component of the SF-36

Domain-specific scales of the SF-36	Factor loadings	Scoring coefficients
Physical functioning	0.177	-0.084
Physical role functioning	0.282	-0.104
Bodily pain	0.327	-0.067
General health perceptions	0.499	0.062
Vitality	0.710	0.280
Social functioning	0.662	0.227
Emotional role functioning	0.579	0.152
Mental health	0.807	0.435
Correlation of the MHC with life satisfaction	0.489***	
Observations	29,303 individuals observed at inclusion	

Notes: Results shown from a factor analysis of the eight domain-specific scales of the SF-36, with a two-factor solution obtained after varimax rotation (mental health and physiological health). The factor loadings are the estimated coefficients of a 'regression' of the domain-specific scale on the two factors. The scoring coefficients are the estimated coefficients of a regression of the unstandardized mental health score on the eight domain-specific scales.

Table A2: Estimation Results (Control variables)

	Dynamic RE model	**Finite mixture dynamic Model**
Log Household Income	0.120**	0.030
	(0.059)	(0.039)
Age/10	0.077	0.734***
	(0.309)	(0.186)
$(Age/10)^2$	0.052**	0.003
	(0.022)	(0.012)
Male	0.177	-0.191***
	(0.111)	(0.055)
Employed: Full-time	0.224**	-0.433***
	(0.107)	(0.067)
Employed: Part-time	0.514***	-0.024
	(0.099)	(0.064)
Unemployed	0.209	-0.006
	(0.198)	(0.142)
University degree	0.152	0.185***
	(0.133)	(0.064)
Certif./Dip. Degree	0.144	0.208***
	(0.116)	(0.060)
12 years of schooling	-0.041	0.050
	(0.165)	(0.081)
Married or cohabiting	0.402***	0.103
	(0.148)	(0.095)
Divorced or separated	0.605***	0.485***
	(0.203)	(0.146)
Number of children	-0.245***	-0.175***
	(0.043)	(0.027)
Other control variables	Year dummies Initial conditions	Year dummies Initial conditions
Observations	6,294 individuals (69,460 individual-waves)	6,294 individuals (69,460 individual-waves)

Notes: Estimation results of the Dynamic Random Effect and the Finite mixture dynamic Models for the sociodemographic control variables. Standard errors in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$. Omitted categories are: female, not active, less than grade 12 schooling, and single.

Table A3: Correlations between Estimated Class Probabilities using the Full and Restricted Samples

	Class 1 (1-17)	**Class 2 (1-17)**	**Class 3 (1-17)**
Class 1 (1-12)	0.8318		
Class 2 (1-12)	-0.4450	0.7765	
Class 3 (1-12)	-0.4472	-0.3123	0.8095

Table A4: Estimates Coefficients on Interaction Terms from Individual Fixed-Effect Regressions of Psychological Health

Specification	**1**	**2**	**3**	**4**	**5**
Panel A			**Financial worsening**		
TPL W1-W12 (z-score)	-0.516*			-0.492*	
	(0.284)			(0.286)	
Prob Class 1 W1-W12		2.212**			2.119**
		(1.021)			(1.074)
LOC(z-score)			-0.259	-0.206	-0.081
			(0.276)	(0.278)	(0.290)
Panel B			**Being fired**		
TPL W1-W12 (z-score)	-0.151			-0.199	
	(0.271)			(0.280)	
Prob Class 1 W1-W12		0.622			0.848
		(0.891)			(0.937)
LOC(z-score)			0.141	0.190	0.219
			(0.266)	(0.275)	(0.280)
Panel C			**Any of the ten adverse life events**		
TPL W1-W12 (z-score)	-0.274***			-0.282***	
	(0.093)			(0.095)	
Prob Class 1 W1-W12		0.982***			1.054***
		(0.306)			(0.320)
LOC(z-score)			-0.020	0.040	0.074
			(0.093)	(0.095)	(0.097)
Observations			21,742		
Individuals			5,388		

Table A5: Impact of Resilience Predicted (Waves 1-12) on New Occurrences of Psychological Health Problems (Waves 13 and 17)

	Depression/Anxiety	**Medication**	**Psychiatrist/psychologist**
Specification 1			
TPL W1-W12 (z-score)	0.030***	0.021***	0.018***
	(0.003)	(0.002)	(0.002)
Prob Class 1 W1-W12	-0.094***	-0.077***	-0.061***
	(0.009)	(0.007)	(0.007)
Specification 2			
TPLW1-W12 (z-score)	0.026***	0.018***	0.018***
	(0.003)	(0.003)	(0.003)
LOC (z-score)	0.015***	0.012***	0.003
	(0.003)	(0.003)	(0.003)
Prob Class 1 W1-W12	-0.082***	-0.068***	-0.060***
	(0.009)	(0.007)	(0.007)
LOC (z-score)	0.014***	0.010***	0.001
	(0.003)	(0.003)	(0.003)
Individuals	7,530	7,987	7,936

Notes: Presented figures are estimated effects of TPL on the probability of depression/anxiety, taking prescription medication for depression/anxiety or having seen a psychiatrist or a specialist, *conditional on not being in this situation four years before* (these questions are asked every four waves). We maximise the number of observations by using outcome-specifict subsamples including all complete cases. Also included in the regression are time fixed-effects, and time-varying controls. *, ** and *** indicate p-values less than 0.1, 0.05 and 0.01.

Appendix B: Technical Appendix

Model specification and likelihood function

Conditional on time-invariant membership in a latent class indexed by *{c,k,l}*, the dynamics of psychological health are assumed to be represented correctly by the following model with non-random and fixed coefficients:

$$H_{it} = \rho_{lc}H_{it-1} + \beta' x_{it} + \mu_{0c}{}' S_{it} + \mu_{1c}{}' S_{it+1} + \lambda w_i + \alpha_{kc} + exp(\sigma_{kc}{}')\tilde{u}_{it}$$
$$\tilde{u}_{it} \sim \text{i.i.d normal}(0,1) \qquad \text{(B.1)}$$

We observe the empirical probabilities $\Pr(H_{i1}, \dots H_{iT} | S_i, x_i, H_{i0}, w_i, z_i)$, where S_i denotes the set of anticipated and contemporaneous adverse events. Given our modelling assumptions, we have the following decomposition of the individual contribution to the sample likelihood:

$$\Pr(H_{i1}, \dots H_{iT} | S_i, x_i, H_{i0}, w_i) \propto$$
$$\sum_{c=1}^{C} p_c \sum_{k=1}^{K_c} \sum_{l=1}^{L_c} \pi_{klc} [\prod_{t=1}^{T} Pr(H_{it} | H_{it-1}, x_{it}, S_{it}, S_{it+1}, w_i, \Theta_i = (\rho_{lc}, \mu_c, \theta_{kc}), \beta, \lambda)] \qquad \text{(B.2)}$$

This decomposition result stems in particular from the first-order Markov condition of no autocorrelation in the error term and independence between psychological health at *t* and *t-2* conditional on psychological health at *t-1*, the contemporaneous values of the covariates (life events at *t* and *t+1*), and the values of the individual random effects. Given independence between the random effects and the error term $\tilde{u}_{it}$, the probability in brackets follows a normal distribution. Denoting the standard normal p.d.f by ϕ, the parameters $\rho_{lc}, \mu_c, \theta_{kc}, \beta, \lambda$ are obtained via maximisation of the following log-likelihood for given values of C, K_c and L_c:

$$\Pr(H_{i1}, \dots H_{iT} | S_i, x_i, H_{i0}, w_i, \beta, \lambda) \propto$$
$$\sum_{c=1}^{C} \sum_{k=1}^{K_c} \sum_{l=1}^{L_c} \underbrace{p_c \pi_{klc}}_{p_{klc}} \left[\prod_{t=1}^{T} \phi \left(\frac{H_{it} - \rho_{lc}H_{it-1} - \beta' x_{it} - \mu_{0c}^{'} S_{it} - \mu_{1c}^{'} S_{it+1} - \lambda' w_i - \alpha_{kc}}{exp(\sigma_{kc}^{'})}\right)\right] \qquad \text{(B.3)}$$

Identification

The parametric model associated with the likelihood function in equation (B.3) is identified from standard results on the identifiability of finite mixtures of exponential laws (Lindsay, 1983). Proving the non-parametric identification of the mixture components in a more general model with a totally flexible error term is beyond the scope of this paper. Nevertheless, Kasahara and Shimotsu (2009) show that finite mixture models of dynamic discrete choice are identified when at least six periods of observation are available, when there is enough variation in the covariates, and when the response pattern of different individuals to similar variations in covariates is truly heterogeneous. In our case, identification also relies on the observation of different patterns of responses to life events by individuals with similar observed characteristics (in particular, similar initial level of psychological health and similar probabilities of adverse events over the observation period). The length of the observation period is key to empirical identification, because it allows us to observe similar individuals with different time sequences of adverse events. Between-individual variations in these sequences help to identify the individual heterogeneity in the distribution of the dynamics of psychological health.

Estimation procedure

Maximising directly the model likelihood in (B.3) will present computational difficulties due to the non-linearity of the model and the number of parameters. We overcome this issue by implementing the iterative EM (Expected Maximisation) algorithm of Dempster and Laird (1977). The intuition underlying this algorithm is that the model would be easier to estimate if individual class membership were perfectly observed: we would just need to estimate linear regression models for each class. Because class membership is unobserved, we have a standard problem of missing data. The EM algorithm solves this problem through a two-step procedure.

In the E-step, expectations of class membership probabilities are constructed for each individual, using all of the information from the data and the model.

E-step*:* For initial values of the parameters $p_{klc}, \rho_{lc}, \beta, \mu_{0c}, \mu_{1c}, \lambda, \alpha_{kc}, \sigma_{kc}$and for each individual, use the parametric specification (B.3) to compute the posterior probabilities:

$$
\begin{aligned}
p_{iklc} &= \Pr(\rho_i = \rho_{lc}, \mu_i = \mu_c, \theta = \theta_{kc} | H_{i1}, \dots H_{iT}, S_i, x_i, H_{i0}, w_i, \beta, \lambda) \\
&= \Pr(\rho_i = \rho_{lc}, \mu_i = \mu_c, \theta = \theta_{kc} | H_{i1}, \dots H_{iT}, S_i, x_i, H_{i0}, w_i, \beta, \lambda) \\
&= \frac{p_{klc} \Pr(H_{i1}, \dots H_{iT} | S_i, x_i, H_{i0}, w_i, \rho_i = \rho_{lc}, \mu_i = \mu_c, \theta = \theta_{kc}, \beta, \lambda)}{\Pr(H_{i1}, \dots H_{iT} | S_i, x_i, H_{i0}, w_i, \beta, \lambda)} \qquad \text{(B.4)}
\end{aligned}
$$

Then, in the M-step, linear regression models can be estimated for each class, with each individual observation being weighted by the expected class membership probability.

M-step: Substitute p_{klc} with p_{iklc} in (B.3) and maximize the log-likelihood to update the parameters $\rho_{lc}, \beta, \mu_{0c}, \mu_{1c}, \lambda, \alpha_{kc}, \sigma_{kc}$. Update p_{klc} by maximizing$\sum_{c=1}^{C} \sum_{k=1}^{K_c} \sum_{l=1}^{L_c} p_{iklc} \, ln(p_{klc})$ with respect to p_{klc} and subject to $\sum_{c=1}^{C} \sum_{k=1}^{K_c} \sum_{l=1}^{L_c} p_{klc} = 1$.

The EM algorithm alternates between these two steps until until convergence, i.e. when the relative difference in two successive set of parameters (Euclidean norm) is less than a tolerance criterion. The variance of the estimator is computed using the empirical information matrix, as proposed by McLachlan and Peel (2000), with computation of likelihood scores at the level of households to account for the panel dimension of the data.

It is well known that the empirical identification of finite mixture models can be difficult, essentially because the likelihood function can be quite flat in some regions of the parameter space. For a better detection of the global maximum of the likelihood function, it is crucial to find good starting values for the individual weights p_{iklc} in the initial M-step. In the phase of model selection, we have experimented with ten different sets of randomly chosen starting weights for each model specification in order to identifiy a global maxima. Tolerance is set to 1e-4 for model selection and, to reduce computing times, we apply a trimming procedure in the M-step by setting p_{iklc} to 0 whenever p_{iklc} is lower than 1e-32. For producing the final estimates, tolerance was set to 1e-6 and no trimming is applied.

Model Selection

There is a lack of guidance from the econometric or statistical theory on the estimation and inference on the optimal number of components in finite mixture models– here on C, K_c and L_c -, which is *a priori* unrestricted.[26] From a pragmatic perspective, finite mixture models can be used for two different purposes, either achieving the best fit to the empirical distribution of data or classifying observations with distinct latent classes that can later be used for predictions. Following McLachlan and Peel (2000, chap. 6), we may use a penalized-likelihood criterion – the Bayesian Information Criterion (BIC) – to select the model that achieves the best fit. Yet, as noted inter alia by Baudry (2015), the BIC "is known to be consistent, in the sense that it asymptotically selects the true number of components, at least when the true distribution actually lies in one of the considered models", but "this nice property may however not suit a clustering purpose" whenever the distribution for each latent class is not gaussian. In that case, using the BIC will tend to favor models with two many classes because "several gaussian components are necessary to approximate each non-gaussian components".When the user of finite mixture models is more interested in clustering in the data into well-separated classes, then decision can be based on an entropy criterion that measures the uncertainty of the assignment of observations into the different classes. For instance, Bruhin et al. (2019) applies an entropy criterion to the selection of the optimal number of distinct profiles of economic preferences from a latent class structural model estimated on experimental data. Finally,

[26] It is not possible to use standard likelihood ratio statistics because it has a non-standard limiting distribution when one compares models with different numbers of components (Liu and Shao, 2003). Recent developments in this area (e.g. Chen et al., 2012) are, to the best of our knowledge, not applicable to our model.

Biernacki et al. (2000) propose using an ICL-BIC criterion, which is the BIC penalized by the entropy (see Etilé, 2006, for an application in economics).

In the present study, model selection is driven by our objective of identifying individual heterogeneity in the relationship between life events and psychological health (slope heterogeneity), while controlling for the confounding effect of both time-varying and constant unobserved heterogeneity (intercept and variance heterogeneity). Hence, we cannot apply an ICL-BIC criterion. In addition, we view the 'latent class' interpretation of the model as a convenient way to discuss the estimation results. Notably however, the latent classes only capture 'ideal' types of psychological response profiles, with all individuals lying somewhere between these ideal classes. Our ultimate aim is to identify *individual* profiles of responses to adverse events through a mixture of these types. It is not to cluster individuals into well-separated clusters. Therefore, we opt for a two-steps procedure that is eventually a mix between economic applications of latent class models that focus on the identification of slope heterogeneity profiles, and econometric papers that view finite mixture distributions as a flexible means of modelling unobserved heterogeneity, and estimate models with large number of support points (see Train, 2008, Bonhomme and Robin, 2009, Etilé and Sharma, 2015). In a first step, for a given structure of slope heterogeneity (C is fixed), we restricted our search on models with the same number of components K_c for all classes[27], and we choose K_c in order to maximize the statistical fit of the model. We here rely on the BIC, and the lower is the BIC the better is the fit. In a second step, we compared the results produced by models with C=2, 3 and 4 slope classes. It is worth noting that a model with two slope classes ($C=2$) and two autoregressive parameters within each of the slope class (L_c=2) is equivalent to a model with four slope classes ($C=4$) with one autoregressive parameter (L_c=1), with a constraint on the slope coefficients μ_c (*i.e.* $\mu_1 = \mu_2$ and $\mu_3 = \mu_4$. Hence, we can examine the results of the four-slope classes model to decide whether it is worth estimating models with L_c>1 for some classes. It turnt out that this is not the case with our data (see below the results of the four-slope classes model).

Table B1 below reports *BIC* values for various specifications. Table B1 shows that the model with C=4 components for modelling the heterogeneity in the short-term impact of life events (μ), and $K_c=8$ for all c, seems to provide the best overall fit (last line). With C =3 and C=2 components for slope heterogeneity, the best fits are obtained for K_c =9 and K_c =10 respectively.

[27] Practically, this decision was driven by constraints in terms of computing time: for instance, estimation of a 4-slopes model can take up to two days on a 16-cores computer, which has to be multiplied by the number of different starting values that are tested.

Table B1: Model selection - BIC

C ↓	Kc →	7	8	9	10	11
2		430198	429915	429816	**429736**	429747
3		429388	429330	**429253**	429265	429301
4		429299	**429209**	429261	429307	429349

In a second step, we compare the classifications and the estimates produced by the three models {C, K_c}={2,10},{3,9 } and {2,8}. We first compute the normalized entropy of the classification into slope classes, $1\text{-}\frac{1}{N\,ln(C)}\sum_i \sum_c p_{ic}\, ln(\, p_{ic})$. The closer it is to 1, the less uncertain the individual assignment into classes is. Slope entropy equals 0.46 for models {2,10} and {4,8} and 0.44 for model {3,9}. Hence, the three models yields similar levels of uncertainty regarding the clustering of individuals. Whatever the model, individuals are not assigned with certainty into one class. These classes represent ideal-types that should be primarily used to understand resilience rather than to categorise individuals perfectly.

We now compare more directly the three models. Each model has a single "resilient" class that corresponds to a low value of the auto-regression parameter (low ρ_{lc}) and small contemporaneous impacts of shocks (low μ_c). Table B2 reports the correlations between the individual probabilities of membership of this most resilient class, across the three models. The probabilities are very close for models {3,9} and {4,8}, with a correlation of 0.92.

Table B2: Correlations between the probabilities of membership of the most resilient class

	{2,10}	*{3,9}*	*{4,8}*
{2,10}	1		
{3,9}	0.83	1	
{4,10}	0.78	0.92	1

We then compare the estimated coefficients across the three models and the "less-resilient" classes. The three-slopes classes model {3,9} has a non-resilient class with low state-dependence/large fluctuation (Class 2) and one with large state-dependence/low-fluctuation (Class 3). The 4 slope-classes model{4,10} essentially divides the former type into sub-types. Table B.3. compares the shares of the different types across models.

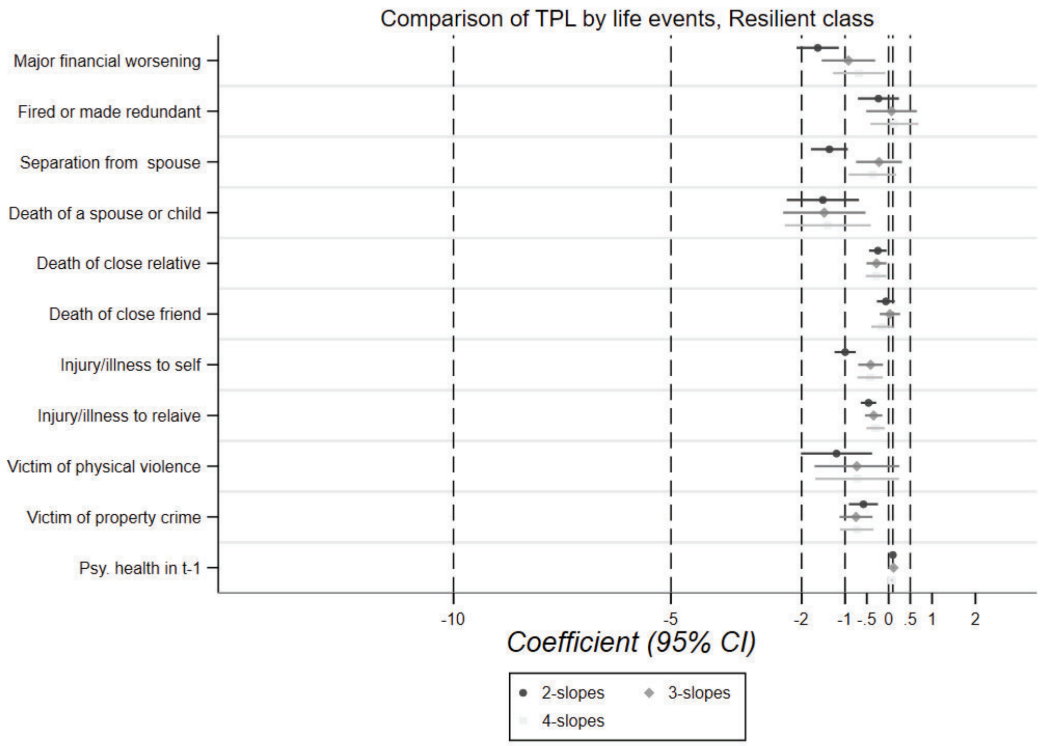
Table B3: Comparison of classifications across models

two-slopes {2,10}	**three-slopes {3,9}**	**4 slopes {4,8}**
Resilient: 47.1%	Class 1: 37.1%	Class 1: 32.4%
Non resilient: 52.9%	Class 2: Large state dep./Low fluct 30.0%	Class 2: 27.6%
	Class 3: Low state dep./Large fluct. 33.9%	Class 3: 30.3%
		Class 4: 9.7%

The correlation between the individual probabilities of membership of Class 2 in model {3,9} and Class 2 in model {4,8} is 0.93. Hence, the three-slopes and four-slopes models differ only with respect to resilience profiles that exhibit little state dependence and large fluctutations.

Last we examine more precisely the differences between the models by comparing the estimated coefficients between classes and between models. Figures B1 to B4 illustrate graphically these comparisons. They display the Total Psychological Losses (TPL) associated to each of the ten events[28], as well as the autoregressive coefficient (last row). Figure B1 shows that the three models produce TPL that are similar for the most resilient classes, except for separation and illness to self that have higher impacts in the two-slope classes model.

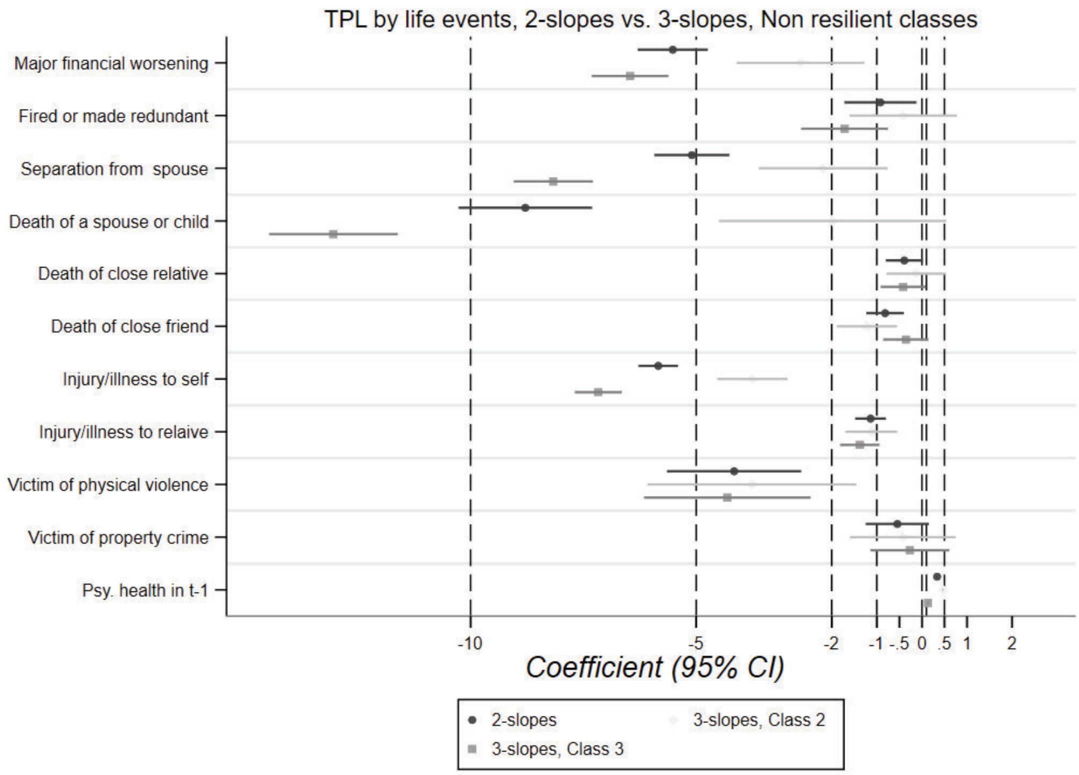
Figure B1: Total psychological loss by event for the most resilient class – model comparison



[28] For each class and each model, the TPL associated to one event is computed as the sum of its anticipated impact and its contemporaneous impact, divided by one minus the autoregressive coefficient.

Figure B2 shows how the non-resilient class of the two-slope classes model splits into two classes of the three-slope classes model. The split is driven by the impacts of financial shock, separation, death of a spouse or a child, illness to self, and, importantly, by lagged mental health. Allowing for three classes instead of two helps to identify resilience profiles that have striking differences.

Figure B2: TPL by event, non-resilient classes – two-slopes vs. three-slopes



Figures B3 and B4 compare the non-resilient classes in the three-slopes and four-slopes models. Figure B3 confirms that the second classes (high state-dependence, smaller fluctuations) are similar in the three-slopes and four-slopes models. Figure B4 shows that there are less gains in moving from a three-slopes to a four-slopes model, than they were in moving from a two-slopes to a four-slopes model. The low-state dependence non-resilient class of the three-slopes model splits into classes 3 and 4 in the four-slopes model. These two classes still exhibit a low state-dependence, with autoregressive parameters close to 0.1. The split is essentially driven by the following events: separation, death of a spouse or a child, illness to self, and to a lesser extent by being victim of a violent crime. In the four-slopes model, for these four events, the TPL is significantly larger in Class 4 than in Class 3.

Figure B3: TPL by event, non-resilient class 2, three-slopes vs. four-slopes

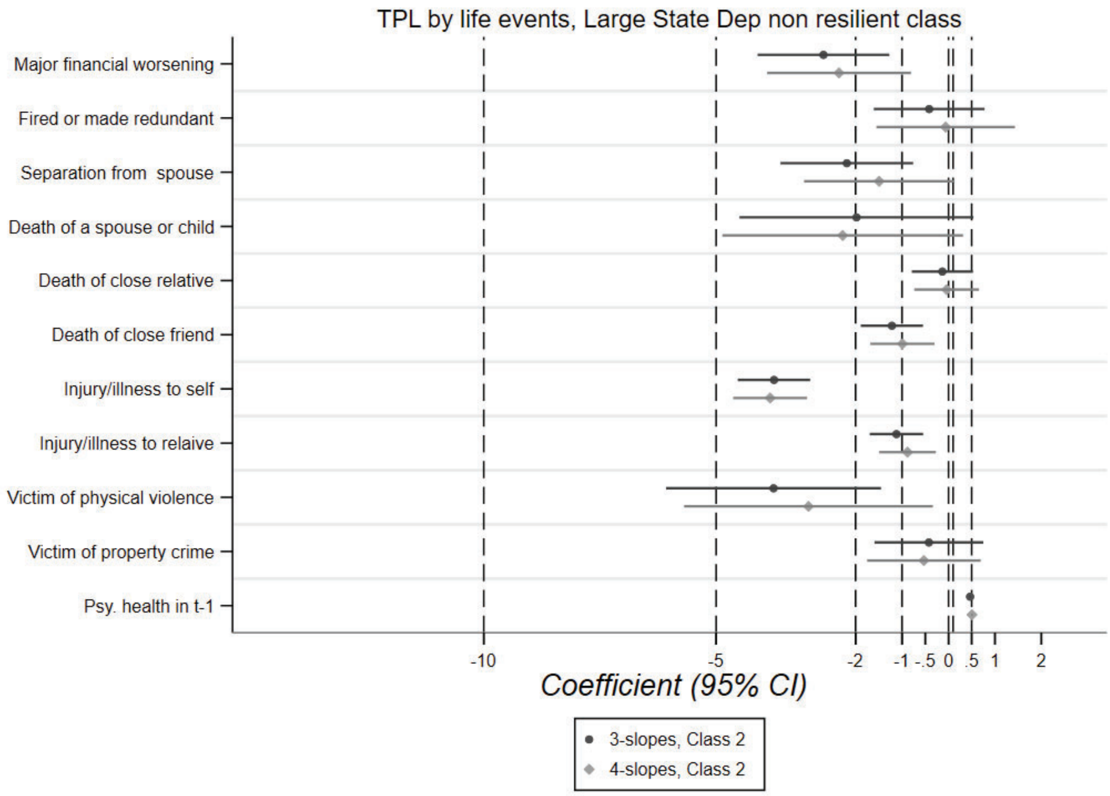
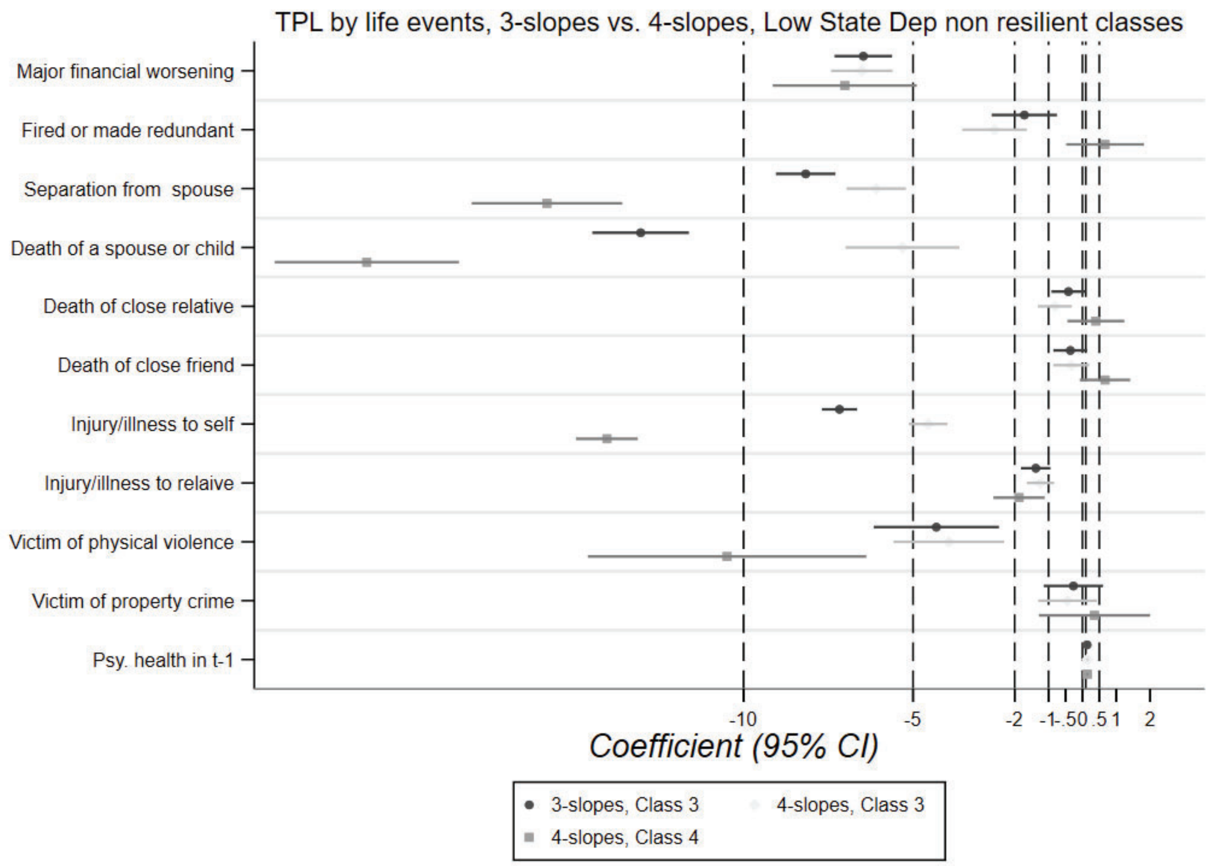


Figure B4: TPL by event, low state dependence non-resilient classes, three-slopes vs. four-slopes



Based on these comparisons, we finally decide to discuss the three-slopes model {3,9} in the main text of the study.

Last, the results of the three-slopes and four-slopes model also show that there is no evidence for a model with four classes that would combine {high, low} state-dependence and {small, large} fluctuations. The fourth class that emerges in the four-slopes model is only a subtype of the low state-dependence/large fluctuation resilience profile. This shows also that we do not need to estimate models with heterogeneity in autoregressive parameters within each slope classes (L_c>1).

Comparison of predicted individual resilience across models

We examine how our resilience measure is is affected by the choice of a two-slopes or four-slopes model instead of the three-slopes model – our preferred specification. Figure B5 provides the distribution of TPL from a standard event (SE) for the two-slopes and four-slopes models. As compared to the three-slopes model (Figure 5), the two-slopes model polarises the distribution between low- and high-resilience individuals, while the four-slopes model adds a long tail to the distribution.

We then compute, for each model, the predicted percentile rank of each individual in the distribution of TPL. We can then compare the individual ranks across specifications to see whether the predicted sorting of individuals by their resilience is stable across models. Figures B6 and B7 displays these rank plots.

In Figure B6, each small grey point is an individual with TPL predicted by the three-slopes model on the x-axis, and TPL predicted by the two-slopes model on the y-axis. The black line is the non-parametric fit curve adjusted to this scatter plot. If moving from the two-slopes model to the three-slopes model preserved the sorting of individuals by resilience, then adding a slope class would produce little benefit. This can be evaluated by examining the departure of the black line from the dashed line. Many individuals with high TPL in the three-slopes model (a TPL above the 70th percentile; low resilience), appear as moderately resilient under the two-slopes model. However, the two-slopes model does poorly in distinguishing the moderately resilient individuals from the least resilient. Figure B7 performs the same exercise for the comparison between the four-slopes and the three-slopes model. It shows that the ranking of individuals is well-prserved when one moves from three-slopes to four-slopes. This confirms that there is little gain in having four slope classes as compared to three slope classes.

Figure B5: Distributions of TPL for two-slopes (left) and four-slopes models (right)

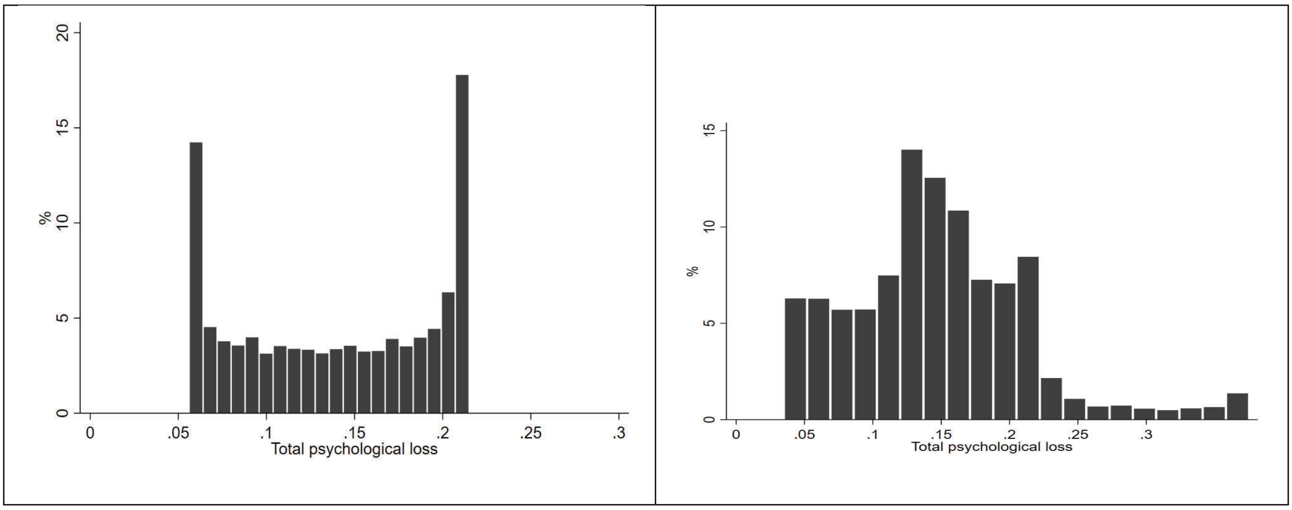


Figure B6: Ranks in the distribution of TPL, two-slopes model *vs. three-slopes* model.

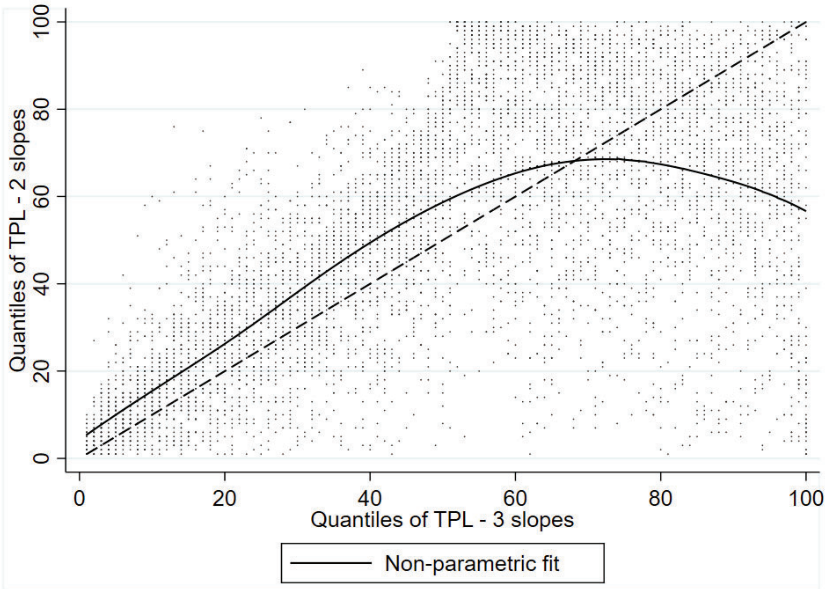
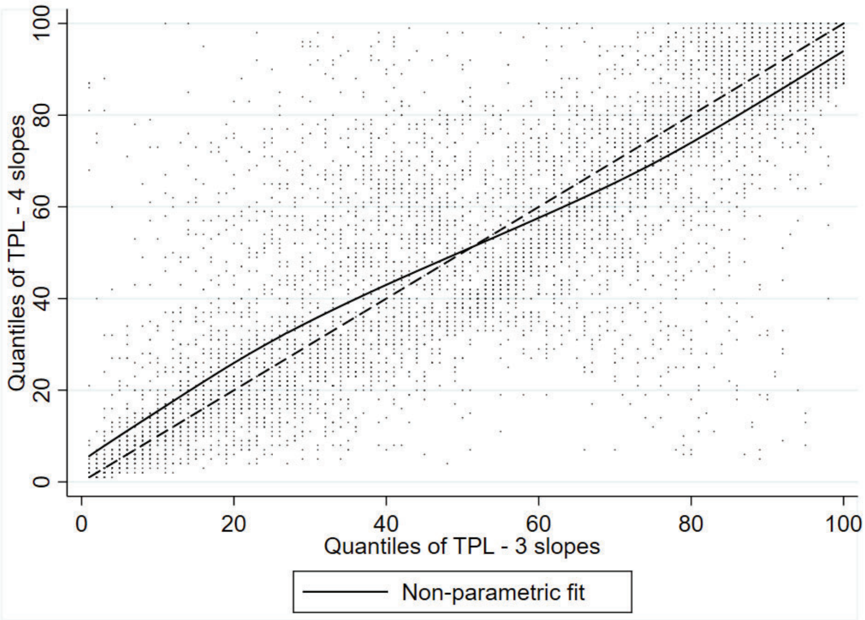


Figure B7: Ranks in the distribution of TPL, four-slopes model *vs. three-slopes* model.



Appendix C: Derivation of Cognitive Ability and Personality Traits

Cognitive ability is measured in Waves 12 and 16 of HILDA using three tests: (1) Backwards Digits Span (BDS) test; (2) a 25-item version of the National American Reading Test (NART); and (3) the Symbol-Digit Modalities (SDM) test. The BDS is a traditional sub-component of intelligence tests and measures working memory span. The interviewer reads out a string of digits, which the respondent has to repeat in reverse order. NART measures pre-morbid intelligence. Respondents have to read aloud and pronounce correctly 25 irregularly spelled words. SDM is a test where respondents have to match symbols to numbers according to a printed key that is given to them. It was originally developed to detect cerebral dysfunction but is now a recognised test for divided attention, visual scanning and motor speed. To derive a summary measure for cognitive ability, we applied a factor analysis to all three test scores, and the first factor is then predicted and standardised to have a mean of zero and a standard deviation of one.

Personality is measured in HILDA in Waves 5, 9, 13 and 17 using a version of the Big-5 Personality Inventory in which 5 personality traits are quantified: extraversion, agreeableness, conscientiousness, openness to experience, and emotional stability (sometimes reversed and labelled neuroticism). Each of these trait variables have been re-scaled to have a mean of zero and a standard deviation of one, with higher scores indicating that the individual is well described by the personality type. Each individuals in our estimation sample is assigned personality values from the earliest possible wave.

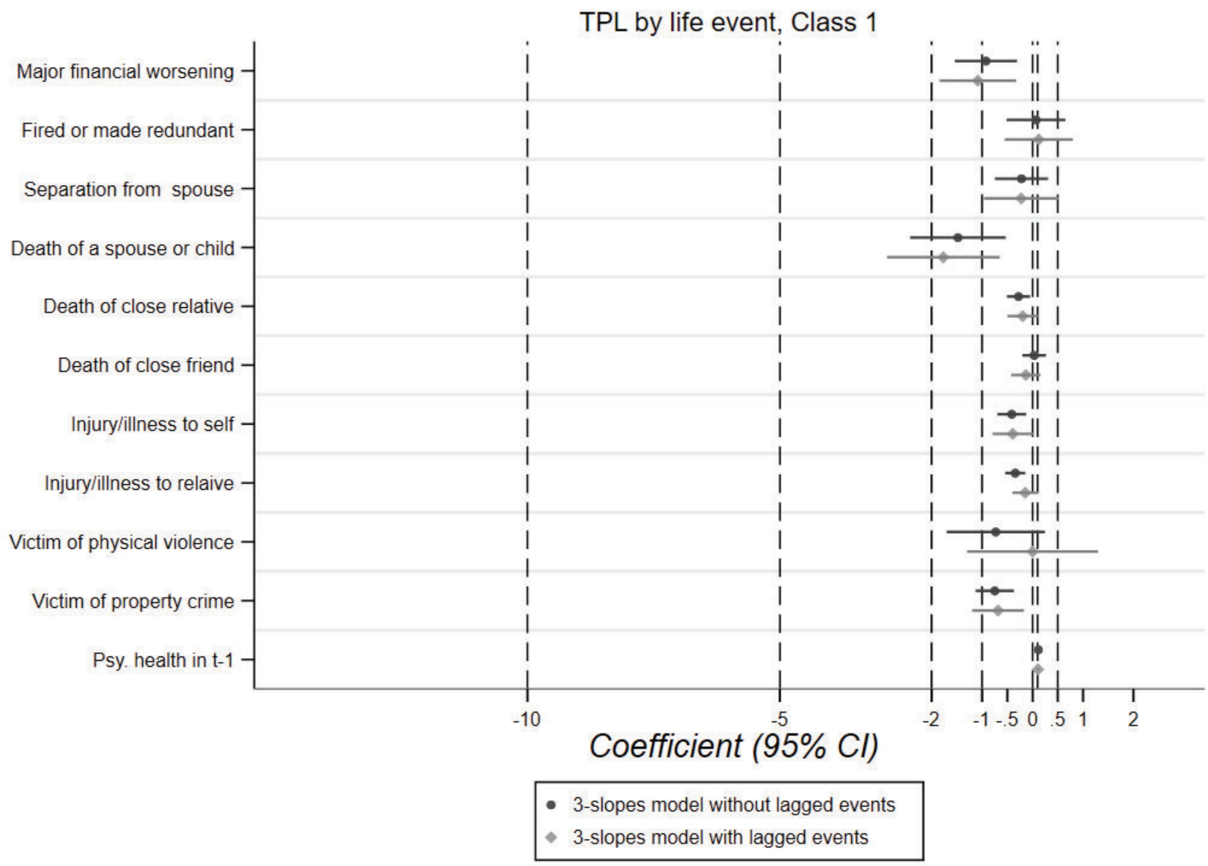
Our second measure of personality (or non-cognitive ability) is locus of control, which is described by Rotter (1966) as a “generalized attitude, belief, or expectancy regarding the nature of the causal relationship between one’s own behavior and its consequences”. It is generated from a locus of control questionnaire included in Waves 3, 4, 7, 11 and 15 that requires respondents to evaluate seven statements (e.g. “I have little control over the things that happen to me”) using a one (strongly disagree) to seven (strongly agree) scale. We add the responses (some items reversed) to form a locus of control index, which is again re-scaled to have mean zero and standard deviation one. Higher scores indicate that the individual has external control tendencies, implying that they believe their outcomes are due to external forces rather than due to their own efforts. As with the Big-5 personality variables, we assign each individual locus of control information from the earliest possible wave.

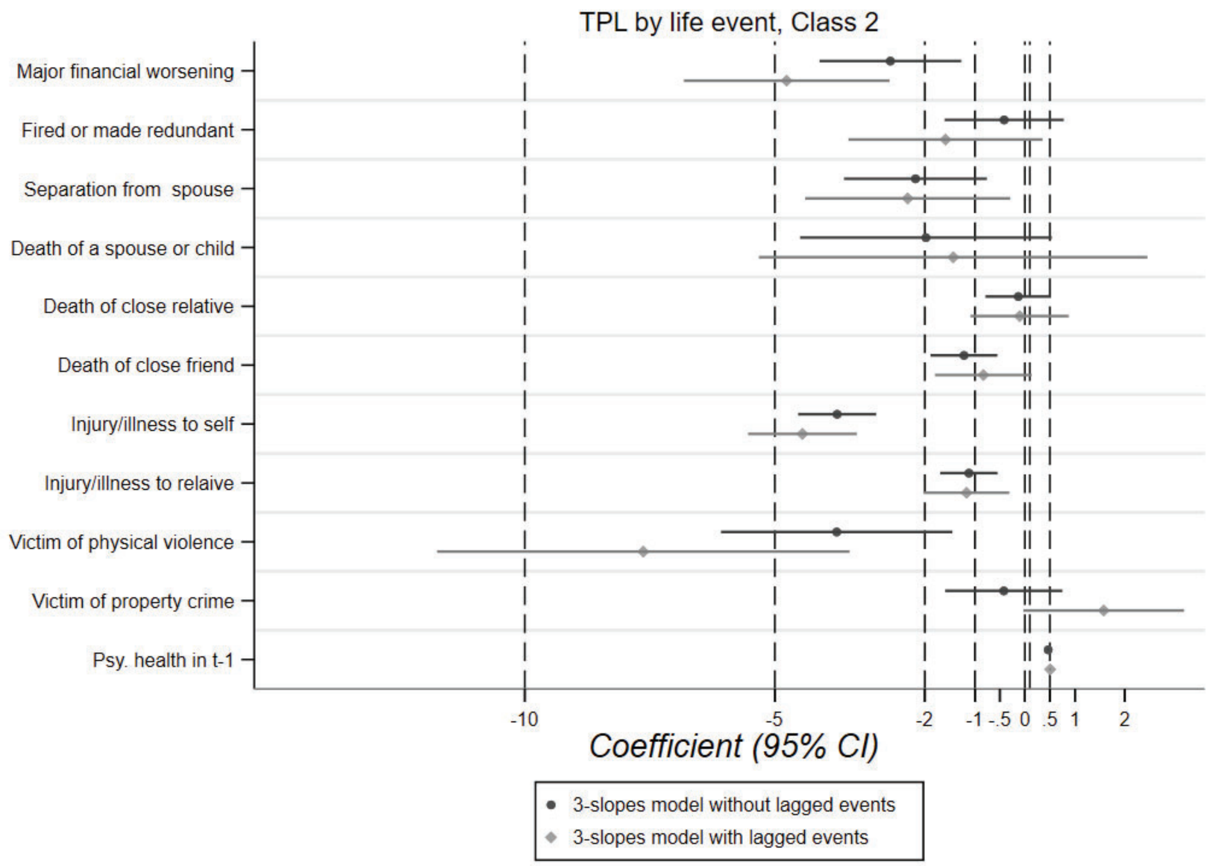
Appendix D: Robustness to the Inclusion of Lagged Events

Our model allows for anticipated and contemporaneous effects of adverse life events, and captures all lagged effects parsimonously through the inclusion of lagged psychological health. However, some events may have specific lagged effects on psychological health, beyond the average state-dependence captured by lagged psychological health. To examine this we have additionally estimated a three-slopes class model that includes lagged events in addition to future and contemporaneous events. The full estimation results are shown in Table D1.

Figures D1 compares the estimated total psychological loss (TPL) for each slope class and each life event between a three-slopes model without lagged life events (our main specification) and the three-slopes model with lagged events. They show that the two specifications deliver similar predictions for all classes. The only notable difference, albeit not significant, is obtained for victim of violence and property crime in Class 2.

Figure D1. TPL by life event with and without adding control for lagged events




TPL by life event, Class 2
Major financial worsening
Fired or made redundant
Separation from spouse
Death of a spouse or child
Death of close relative
Death of close friend
Injury/illness to self
Injury/illness to relaive
Victim of physical violence
Victim of property crime
Psy. health in t-1
-10
-5
-2
-1
-.5
0
.5
1
2
Coefficient (95% CI)
3-slopes model without lagged events
3-slopes model with lagged events

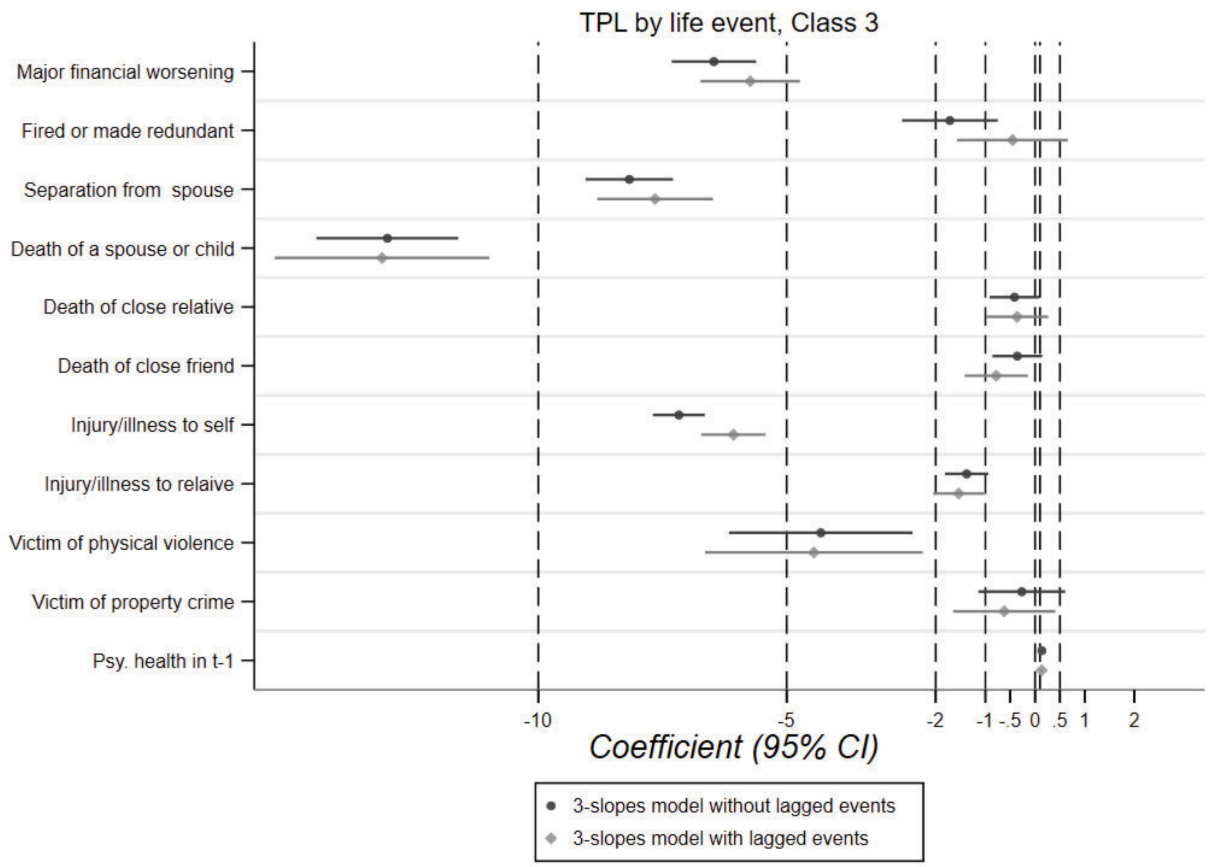

TPL by life event, Class 3
Major financial worsening
Fired or made redundant
Separation from spouse
Death of a spouse or child
Death of close relative
Death of close friend
Injury/illness to self
Injury/illness to relaive
Victim of physical violence
Victim of property crime
Psy. health in t-1
-10
-5
-2
-1
-.5
0
.5
1
2
Coefficient (95% CI)
3-slopes model without lagged events
3-slopes model with lagged events

Table D1 reports the estimated coefficients on all lagged, contemporaneous and future events. The coefficients on lagged events are generally not statistically significant. However, there are a few exceptions, as well as minor changes in the estimated contemporaneous and anticipated effects of events. If we focus on estimates that are significant at the 5% level, being fired, a victim of physical violence, and own injury have significant lagged negative effects in Class 2. This suggests that these events have specific long-lasting effects that are not fully captured by the high estimated autoregressive parameter for this class. In Class 3, separation from spouse and illness to self have lagged positive effects on psychological health, suggesting that some past adverse events may provide material for an increase in well-being.

Table D1: Estimation results, models with vs. without one-period lags of adverse life events

Model with lagged events		c=1 With	c=1 Without	c=2 With	c=2 Without	c=3 With	c=3 Without
		Lagged Psychological Health Parameter (ρ_i)					
Psychological health in *t*-1		0.109***	0.115***	0.505***	0.465***	0.136***	0.136***
		(0.008)	(0.007)	(0.009)	(0.009)	(0.009)	(0.008)
		Immediate, Anticipation and Lagged Parameters					
Major financial worsening	*t*	-0.204	-0.528**	-1.329***	-0.942***	-4.599***	-4.910***
		(0.206)	(0.211)	(0.304)	(0.295)	(0.262)	(0.269)
	t+1	-0.387**	-0.288	-0.483	-0.498*	-0.756***	-0.674**
		(0.196)	(0.181)	(0.354)	(0.303)	(0.286)	(0.285)
	t-1	-0.372*	-	-0.544*	-	0.402	-
		(0.209)		(0.321)		(0.297)	
Fired or made redundant	*t*	0.241	0.377*	-0.081	-0.004	-0.906***	-1.119***
		(0.193)	(0.193)	(0.312)	(0.244)	(0.279)	(0.278)
	t+1	-0.480***	-0.315*	-0.006	-0.219	0.004	-0.362
		(0.179)	(0.180)	(0.295)	(0.241)	(0.315)	(0.326)
	t-1	0.348*	-	-0.698**	-	0.512	
		(0.182)		(0.298)		(0.333)	
Separation from spouse	*t*	-0.200	-0.288	-0.622*	-0.311	-5.217***	-4.766***
		(0.216)	(0.193)	(0.335)	(0.306)	(0.287)	(0.275)
	t+1	0.093	0.094	-0.724**	-0.860***	-2.409***	-2.288***
		(0.211)	(0.194)	(0.326)	(0.282)	(0.311)	(0.314)
	t-1	-0.093	-	0.186	-	1.018***	-
		(0.194)		(0.329)		(0.323)	
Death of spouse or child	*t*	-0.528	-0.552*	-1.538**	-1.282**	-9.222***	-9.687***
		(0.326)	(0.317)	(0.605)	(0.499)	(0.476)	(0.413)
	t+1	-0.689**	-0.756***	0.300	0.222	-1.703***	-1.574***
		(0.270)	(0.261)	(0.528)	(0.496)	(0.546)	(0.474)
	t-1	-0.355	-	0.529	-	-0.431	-
		(0.297)		(0.618)		(0.572)	
Death of close relative	*t*	-0.106	-0.149**	-0.330**	-0.192	-0.481***	-0.411**
		(0.076)	(0.075)	(0.147)	(0.125)	(0.162)	(0.165)
	t+1	-0.072	-0.097	0.192	0.122	-0.023	0.053
		(0.079)	(0.077)	(0.150)	(0.132)	(0.173)	(0.168)
	t-1	0.003	-	0.086	-	0.192	-
		(0.078)		(0.145)		(0.169)	
Death of close friend	*t*	0.005	0.086	-0.136	-0.449***	-0.254	-0.210
		(0.077)	(0.076)	(0.163)	(0.132)	(0.176)	(0.166)
	t+1	-0.067	-0.057	-0.183	-0.202	-0.195	-0.098
		(0.078)	(0.077)	(0.154)	(0.132)	(0.179)	(0.176)
	t-1	-0.056	-	-0.092	-	-0.226	-
		(0.079)		(0.154)		(0.182)	
Injury or illness to self	*t*	-0.520***	-0.254***	-0.340**	-1.167***	-4.856***	-5.161***
		(0.098)	(0.094)	(0.173)	(0.158)	(0.167)	(0.161)
	t+1	-0.004	-0.110	-0.858***	-0.842***	-1.125***	-1.032***
		(0.106)	(0.094)	(0.175)	(0.159)	(0.175)	(0.175)
	t-1	0.174	-	-1.002***	-	0.737***	-
		(0.111)		(0.181)		(0.190)	

Injury or illness to relative	*t*	-0.111	-0.179***	-0.644***	-0.496***	-1.007***	-1.051***
		(0.069)	(0.065)	(0.130)	(0.112)	(0.141)	(0.139)
	t+1	-0.101	-0.125*	-0.104	-0.103	-0.339**	-0.138
		(0.070)	(0.069)	(0.132)	(0.117)	(0.147)	(0.152)
	t-1	0.082		0.171		0.019	
		(0.067)		(0.131)		(0.142)	
Victim of physical violence	*t*	0.008	-0.319	-1.531***	-1.411***	-2.965***	-2.630***
		(0.360)	(0.299)	(0.564)	(0.482)	(0.534)	(0.512)
	t+1	-0.094	-0.326	-0.621	-0.603	-1.517**	-1.095*
		(0.354)	(0.297)	(0.571)	(0.518)	(0.600)	(0.611)
	t-1	0.087		-1.622***		0.635	
		(0.345)		(0.499)		(0.521)	
Victim of property crime	*t*	-0.244*	-0.428***	0.045	0.265	-0.156	-0.069
		(0.141)	(0.124)	(0.254)	(0.229)	(0.307)	(0.291)
	t+1	-0.165	-0.234*	-0.087	-0.490**	-0.373	-0.161
		(0.133)	(0.127)	(0.275)	(0.221)	(0.295)	(0.282)
	t-1	-0.198		0.821***		-0.006	
		(0.137)		(0.260)		(0.267)	

Notes: Columns 1,3, and 5 report the estimated coefficients of the finite mixture dynamic model for classes 1 to 3 respectively, for a specification that includes the one-period lags of life events. Columns 2, 4 and 6 report for comparison purpose the results of the specification without lagged events (repeated from Table 2). This table only reports the coefficients on lagged psychological health, and contemporaneous and future life events. The full esults are available upon request. In both models, we include as additional control variables with homogenous effects (see Table A2): logarithm of household income, age, age squared, male, labour market status (full-time employment, part-time employment, unemployment, inactive (reference)), degree (university, vocationnal diploma, high-school, less than grade 12 (reference)), marital status (partnered, divorced or separated, single (reference)), number of children at home, year dummies. In both models, we also control for initial conditions by including the initial level of psychological health, as well as the individual average of all time-varying variables. Standard errors in parentheses. *, ** and *** denote statistical significance at the 0.10, 0.05 and 0.01 levels, respectively.