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Abstract

Using a novel, dynamic finite mixture model applied to 12 years of nationally representative panel data, we explore individual heterogeneity in the total psychological response (our measure of resilience) to ten major adverse life events, including serious illness, redundancy and crime victimisation. Importantly, this model takes into account that individuals are not randomly selected into adverse events, that some events are anticipated in advance of their occurrence, and that the immediate psychological response and the speed of adaptation may differ across individuals. Additionally, we generate a 'standardised event' in order to document the distribution of general resilience in the population. We find considerable heterogeneity in the response to adverse events, with the total psychological loss of people with low resilience being several times larger than the average loss. We also find that resilience is strongly correlated with clinical measures of mental health, but only weakly correlated with cognitive and non-cognitive traits. Finally, we find that resilience in adulthood to some extent is predictable by childhood socioeconomic circumstances; the strongest predictor we identify is good childhood health.

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1. Introduction

Nearly everyone will experience a major adverse life event, such as a divorce, redundancy, serious injury or accident, being a victim of crime, or the death of a close friend. Individuals and communities also may be victims of natural disasters, civil conflict, or such criminal acts as mass shootings and terrorism. How well do individuals cope with such events, and do some suffer significantly more than others? The existing literature has found that the majority of people do not experience subsequent severe psychological trauma or mental illness (see, for example, Rutter, 1985, 1987; Masten, 2001; Bonanno et al., 2010, 2015). Rutter (1985) summarised this, noting the "universal observation that even with the most severe stressors and the most glaring adversities, it is unusual for more than half of children to succumb. The same recognition has applied to adults to the development of depression following personal losses and rebuffs. Although risk of depression following disturbing adverse events is increased, it is usual for most people not to become depressed in spite of the stressful experiences".[1]

The psychology literature often describes the variation in how individuals respond to adversities as capturing 'psychological resilience' (Fletcher and Sarkar, 2013, and Bonnano et al., 2015, provide recent reviews). Bonanno (2004) in fact defines resilience 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."[2] Indeed, documenting the distribution of resilience in the population in the context of different adverse events, and identifying the characteristics of individuals with different levels of resilience, is a valuable research task. As Clark (2016) notes, "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. More broadly, Fletcher and Sarkar (2013) suggest that governments should provide community-based opportunities that enable individuals to access environmental and personal resources that develop resilience. Examples of policy-related initiatives could include public education campaigns, mentorship programs for young people, and social groups for the elderly. The idea of building

[1] Similarly, Masten (2001) describes the ability of the majority of children to overcome significant adversity as arising from "ordinary magic", with individuals being capable of "astonishing resistance, coping, recovery, and success in the face of adversity, equipped with the usual human adaptational capabilities and resources, functioning normally" (Masten and Powell, 2003).

[2] However, Bonanno (2012) provides a discussion of the "uses and abuses" of the resilience construct. Fletcher and Sarkar (2013) note that, "One of the main difficulties in conducting research on resilience is that wide discrepancies exist in the way that resilience is defined and conceptualized." For example, there is some debate about whether resilience should be conceptualised as a personality trait, or rather as a dynamic process, and the extent to which resilience is context-specific (see, for example, Jacelon, 1997; Luthar, 2000; Luthar et al., 2000; Fletcher and Sarkar, 2013). For an inter-disciplinary panel discussion of the definition of resilience, see Southwick et al. (2014).

resilient communities is now a strategic goal of many national governments (see, for example, Longstaff et al., 2010; Cutter et al., 2013).

In this paper we use a novel, dynamic finite mixture model applied to 12 years of data from a rich, nationally representative panel survey, to explore in detail the extent of individual heterogeneity in the psychological response (or level of resilience) to ten major adverse events. We also define a global measure of resilience as the expected inter-temporal loss of psychological health due to a 'standardised' event (SE), and derive from that a distribution for the population. Our model allows for heterogeneity in both anticipation and adaptation responses, while also attempting to account for the initial conditions problem and selection into events. We then document the relationship between resilience and adult socioeconomic characteristics, explore the distinctiveness of resilience from measures of cognitive ability and non-cognitive traits that have been the focus of a growing economics literature in recent years, and finally we relate individual-level adulthood resilience to one's childhood to better understand the extent to which resilience can be predicted by childhood socioeconomic characteristics. We believe that these analyses provide a useful integration of the limited literature on resilience in economics with the large psychology literature on this important topic.[3]

Two broad aspects of resilience are explored in the psychology literature. First, there are studies of the differential outcomes of children growing up with adversity and socioeconomic disadvantage. Second, there are studies of the factors that help to explain why adults, and to a lesser extent communities, differ in their psychological reactions to adversities and stresses (see, for example, Rutter, 1985, 1987; Cicchetti and Rogosch, 1997; Luthar et al., 2000; Masten, 2001; Charney, 2004; Martinez-Torteya et al., 2009; Bonanno, 2012; Banny et al., 2013; Cicchetti, 2013; Amstadter et al., 2014; Howell and Miller-Graff, 2014; Bonanno et al., 2015). According to Masten (2007) there have been four waves of resilience research, the most recent focusing on multi-level analysis and the dynamics of adaptation. Importantly, it has found that the factors explaining resilience are complex and multi-dimensional, spanning genetic, neurobiologic, temperamental, and environmental influences (Caspi et al., 2003; Charney, 2004; Boardman et al., 2008; Banny et al., 2013; Amstadter et al., 2014). It is most salient for policy interventions that resilience is seen to be modifiable to some extent on both individual and cultural levels (Connor and Zhang, 2006; Netuveli et al., 2008).

Moreover, some papers have focused on identifying distinct types or classes of individuals according to how they respond to adverse events. One of most researched is bereavement. In terms of the psychological response to the death of a spouse, Bonanno (2004) identified five distinct

[3] We recognise that resilience has been studied by many disciplines, but this review focuses mainly on the psychology literature.

response profiles; 35% of individuals experience significant trauma (classed as 'chronic depression') before and after the loss, while 46% suffer no trauma ('classified as resilient'). More recent research has found that 69% of individuals are resilient following the death of a spouse or child (Maccallum et al., 2015). Reviewing the literature on natural disasters, Bonanno et al. (2010) conclude that serious psychological harm rarely affects more than 30% in most samples, and "often more than half of those exposed, experience only transient distress and maintain a stable trajectory of healthy functioning or resilience." A third example is post-traumatic stress following a mass college campus shooting. Here, Orcutt et al. (20014) identify four response trajectories: 61% of students are classed as 'minimal impact-resilience'; 29% as 'high impact-recovery'; 8% as 'moderate impact-moderate symptoms'; and 2% as 'chronic dysfunction'.

However, many studies in the resilience literature examine the psychological response to a single particular event (or type of event), sometimes using small case-study samples.[4] This means that any conclusions made about the distribution of resilience are likely to be context- (and potentially sample-) specific, and therefore difficult to generalise to a population distribution. This is important because an individual's psychological response may differ by the nature of the life event, being resilient in some aspects of life, but not others. By focusing on the psychological response to ten major events using nationally representative data, we aim to provide a more general picture of the heterogeneity of resilience in the population.

A distinct but related literature has focused on measures of subjective wellbeing rather than mental health conditions. In particular, researchers have looked at variation in life satisfaction and hedonic adaptation to life events, with concepts of the hedonic treadmill and set-point theory[5] being proposed to explain the "general propensity of human beings to return to a set-point of well-being relatively quickly after even the most aversive or auspicious life events" (Mancini et al., 2011).[6] In the economics literature, Clark et al. (2008a) and Clark (2016) provide detailed reviews of research on adaptation, with particular emphasis on the role of reference points (e.g. colleagues, peers, or an individual's own past). These studies have tended to analyse large nationally representative panel surveys to illustrate life satisfaction profiles or trajectories, with particular attention on adaptation to

[4] Some illustrations of the breadth of events studied are: bereavement, divorce (Mancini et al., 2011), chronic pain (Zhu et al., 2014), injury (Quale and Schanke, 2010; Bonanno et al., 2012), the 9/11 New York attack (Bonano et al., 2006; Norris et al., 2009), mass shootings (Norris and Stevens, 2007; Reifels et al., 2013), floods (Norris et al., 2009), droughts (Arouri et al., 2015), volcanic events (Paton et al., 2011), earthquakes (Hogg et al., 2016) and community violence (O'Donnell et al., 2002). Many studies also have focused on the resilience of war veterans (Pietraz et al., 2009; Tsai et al., 2015).

[5] See Brickman and Campbell (1972), Lykken and Tellegen (1996), Diener et al. (1999, 2006), Lucas et al. (2003, 2004); Lucas (2005, 2007) and Mancini et al. (2011).

[6] Another related literature explores the extent of variability in adult subjective wellbeing. For example, Lucas and Brent Donnellan (2007) find that around 35% of the variance in life satisfaction is trait variance that does not change over time, with an additional 29-34% accounted for by a moderately stable component (also see Fujita and Diener, 2005).

income, unemployment and disability. Because of the availability of long panels, Australia (Frijters et al., 2011; Buddelmeyer and Powdthavee, 2016), Britain (Oswald and Powdthavee, 2008; Clark and Georgellis, 2013), and Germany (Clark et al., 2008b; Vendrik, 2013; Qari, 2014), have been the focus of much of this literature. This literature shows clear evidence of adaptation to major events, and in many cases full adaptation, but this is not always the case. Using an individual fixed effects panel model with leads and lags, Clark et al. (2008b) found full adaptation (i.e. a return to baseline satisfaction) to marriage, divorce, widowhood, birth of a child, and layoff within five years for both men and women, but a longer lasting adverse effect on life satisfaction of unemployment for men. Using a similar model, Frijters et al. (2011) found near full adaptation within two years for most major life events. However, recent research by Clark et al. (2016) using German panel data found little evidence of adaptation within a poverty spell.

Most of these studies focus only on the conditional-mean response to life events, rather than the extent of heterogeneity that we address in this paper. In the conclusion of their study, Clark et al. (2016) call for more research on heterogeneous responses, including analysis by socioeconomic background and personality types. In the psychological literature, Bonanno et al. (2015) similarly note, "Average-level scores typically fail to capture heterogeneity in longitudinal distributions, and, more important, fail to identify resilient trajectories or other longitudinal patterns that bear little resemblance to the average pattern of change."

To date we are aware of few economic studies that investigate either the determinants of resilience or the population distribution of resilience. In one important theoretical contribution, Graham and Oswald (2010) propose a theory of hedonic adaptation and resilience to explain how individuals recover psychologically from adverse events. In their model, individuals have a stock of hedonic capital that they can invest in themselves or have invested in by others (e.g. parents, schools, communities, government), for example through socially positive activities (e.g. spending time with friends; undertaking charitable works). This hedonic capital is drawn upon to cope with adverse events, potentially becoming depleted when a sequence of adverse events occurs, which then triggers large psychological losses and lower wellbeing. In contrast, the framework of Cunha and Heckman (2009) points to resilience as a non-cognitive trait, or a skill that can be invested in early in life but which is relatively stable in adulthood.

In one of the few empirical economics papers on resilience, Powdthavee (2014) asks: do childhood characteristics predict psychological resilience to economic shocks in adulthood? Using British panel data, he finds that the effect of unemployment on mental health and life satisfaction is significantly less adverse for individuals who during adolescence had a good relationship with their father or an unemployed mother. Buddelmeyer and Powdthavee (2016) use Australian panel data to investigate whether the effect of adverse events differs for adults with an internal locus of control.

They find that having an internal locus of control moderates the psychological losses associated with some events, particularly when a close family member is detained in jail. There is also a related literature on the extent to which families, local communities, and social networks informally insure individual consumption and wellbeing against negative events (see, for example, Gertler and Gruber, 2002; Clark and Lelkes, 2005; Dehejia et al., 2007). In particular, Dehejia et al. (2007) find that individuals who attend religious services are better able to insure against income shocks.

As mentioned earlier, this paper aims to shed additional light on the extent to which adults differ in their psychological response to major adverse events, and how well this heterogeneity can be predicted by their childhood circumstances. Bonanno et al. (2015) state that in order to provide a useful framework for understanding psychological resilience, a study must explicitly reference each of four temporal elements: baseline or pre-adversity functioning; the actual aversive circumstances; post-adversity resilient outcomes; and predictors of resilient outcomes. With these practical criteria in mind, we analyse nationally representative panel data from the Household, Income and Labour Dynamics in Australia (HILDA) survey, which tracks adult respondents from 2001 to 2012. We estimate the distribution of psychological resilience in the population with respect to ten major adverse events. In order for us to undertake this study, respondents provide information about the adverse events they have experienced in the last 12 months. The ten 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 43% of respondents report experiencing at least one of these adverse events within our panel window.

Our empirical methodology expands on the latent class approach used in a small number of economics papers that explore heterogeneous responses in satisfaction (Clark et al., 2005; Brown et al., 2014)[7], and on the latent growth mixture modeling approach used by psychology researchers to explore resilience (see Bonanno et al., 2010; Galatzer-Levy et al., 2010; Mancini et al., 2011l Galatzer-Levy and Bonnanno, 2012). We thus identify considerable heterogeneity in the psychological response to major adverse events, but find that the majority of individuals bounce back quickly to their pre-event psychological health. Moreover, low resilience is strongly correlated with having a mental health condition, but is only weakly correlated with cognitive and non-cognitive traits. Finally, we find that childhood characteristics, including socioeconomic status, significantly predict adulthood resilience. By far the most important factor linked with being a

[7] Clark et al. (2005) use latent class techniques to allow for slope and intercept heterogeneity in the relationship between income and subjective wellbeing as applied to panel data from twelve European countries. They identify four classes of individuals, with individual characteristics and country of residence being significant predictors of class membership.

resilient adult is having good childhood health. That finding provides additional support for the importance of investing in child health, since a number of studies have also found that childhood health is strongly linked to economic outcomes in adulthood (for example, Case et al., 2005; Goodman et al., 2011).

The remainder of the paper is set out as follows. Section 2 provides a detailed description of our empirical methodology, including our definition of resilience. Section 3 describes the data; Section 4 presents the main results on heterogeneity. In Section 5 we discuss how well adulthood resilience is predicted by childhood characteristics. Section 6 concludes.

2. Empirical strategy and econometric methods

Our empirical strategy has three main stages. First, we develop a dynamic finite mixture model to identify individual heterogeneity in the observed fluctuations in psychological health that follow adverse life events. Second, we derive an individual measure of resilience based on total psychological loss from a standardised event (SE). Third, we investigate the correlations of this measure of psychological loss with clinical measures of mental health, and cognitive and non-cognitive personality traits, and then with childhood characteristics and circumstances.

2.1 Modelling the dynamics of psychological health

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

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

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 focused on the impact of lagged adverse events and the extent to which individuals adapt over time (see, for example, Clark et al., 2008b; and Frijters et al., 2011). 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 standard model by adding heterogeneity in the anticipation of and response to adverse events through the introduction of random coefficients, and by allowing the error-term variance to be individual-specific:

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

where the coefficients $\rho_i, \mu_{i0}, \mu_{i1}, \delta_i$ 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. (2008b) and Frijters et al. (2011), and others, have shown that wellbeing also changes 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.

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, and we refrain from interpreting its determinants causally); (2) anticipation and immediate (short-term) reactions to each adverse event, as accounted for by the parameter vectors μ_{i0} and μ_{i1}; (3) average adaptation

[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 was clearly not possible to model and identify explicitly the probabilities of occurrence of life events. This would have required the identification of 2^{10}-1 probabilities of transition.

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.[9]

2.2. A dynamic finite mixture model

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:

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

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. Our measure of individual heterogeneity in adaptation to life events (resilience) will not reflect individual ability to affect the occurrence of events (self-selection).[10]

The parameter vector $\Theta_{\mathrm{i}} = (\rho_i, \mu_i, \alpha_i, \sigma_i)$ is distributed according to a joint density function *f(Θ*$_i$*)* 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.[11] We therefore let the marginal density h be represented by a finite number C of points $\{\mu_1, \mu_2, \dots, \mu_C\}$ with associated mass probabilities $\{p_1, p_2, \dots, p_c\}$. Hence:

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

[9] An alternative empirical strategy would model psychological health as a function of a set of variables representing adverse life events, a set of lag and lead variables for each event (to capture anticipation and adaptation), a set of variables for childhood circumstances and personality traits, and all of the interactions among the sets. However, given the large number of variables in each set, a fully specified model would include hundreds of variables. In practice, to make such a model tractable and interpretable would require a sequential selection process of the relevant interaction variables with a high probability of misspecification. In addition, preliminary regressions reveal that this approach is plagued by problems of near multi-collinearity. The more parsimonious model in equation (2) has the added advantage of having a more natural interpretation.

[10] 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.

[11] 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.

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 $\{\pi_{klc}; k = 1, \ldots, K_c; l = 1, \ldots, L_c\}$:

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

The literature often takes a 'latent class' interpretation of these distributional assumptions, 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}) reactions to adverse events, and in the baseline level and volatility of psychological health (θ_{kc}). With individual class membership unobserved, these population classes are latent. 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:

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

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.

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

$$\begin{aligned} &\Pr(H_{i1}, \ldots H_{iT} \mid S_i, x_i, H_{i0}, w_i) \propto \\ &\sum_{c=1}^{C} p_c \sum_{k=1}^{K_c} \sum_{l=1}^{L_c} \pi_{klc} \left[\prod_{t=1}^{T} \Pr\left(H_{it} \middle| H_{it-1}, x_{it}, S_{it}, S_{it+1}, w_i, \Theta_i = \left(\rho_{lc}, \mu_c, \theta_{kc}\right), \beta, \lambda\right) \right] \end{aligned} \tag{7}$$

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:

$$\sum_i \log\left(\sum_{c=1}^{C} p_c \sum_{k=1}^{K_c}\sum_{l=1}^{L_c} \pi_{klc}\left[\prod_{t=1}^{T} \phi\left(\frac{H_{it} - \rho_{lc}H_{it-1} - \beta' x_{it} - \mu_{0c}' S_{it} - \mu_{1c}' S_{it+1} - \lambda' w_i - \alpha_{kc}}{\exp(\sigma_{kc}' z_i)}\right)\right]\right) \quad (8)$$

Importantly, this dynamic finite mixture 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.

2.3. Identification, estimation and model selection

The parametric model associated with the likelihood function in equation (8) is identified from standard results on the identifiability of finite mixtures of Gaussian laws.[13] 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 adverse 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-individuals variations in these

[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 C, 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] See Lindsay (1983) for results on the parametric identification of mixtures of exponential laws. Note that the model is parametrically identified only using the first two waves.

sequences help to identify the individual heterogeneity in the distribution of the dynamics of psychological health.

The model likelihood in (8) is highly non-linear and has many parameters, and so is difficult to maximise directly. We therefore apply 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. 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. The EM algorithm alternates between these two steps until convergence to a maximum. We carefully conducted several replications of the maximisation using different sets of starting values in order to detect the global maximum of the likelihood function. We compute the matrix of variance-covariance of the coefficients using Louis formula (Louis, 1982); more details are provided in Appendix B.

One practical issue is the optimal number of support points C, $\{K_c\ ;\ c=1,\dots,C\}$ *and* $\{L_c\ ;\ c=1,..C\}$. Estimating all possible models would have required prohibitively large computing time, so we restricted our attention to models with an equal number of intercept classes within each slope class, and with C=2 or C=3. For C=2 and L_1=L_2=1, we estimated variants with K_c ranging from 1 to 8 support points. For C=2 and L_1=1, L_2=2, we estimated variants with up K_c ranging from 1 to 6 support points. For C=3, we did not allow for additional heterogeneity in the autoregression parameter (L_1=L_2=L_3=1), and there are up to K_c= 6 support points. The total number of support points therefore varies from two to 16. Adding additional points generated problems for locating a global maximum with no significant informational gains, and the mass associated with these points tended to be close to zero. We then applied a Bayesian Information Criterion (BIC) to choose between models (McLachlan and Peel, 2000). It is computed as $BIC = -2 * \measuredangle(k) + k * \ln(n)$ where $\measuredangle(k)$ is the likelihood of the model, k is its number of parameters and n is the number of observations. Eventually we retained a specification with C=3 and L_1=L_2=L_3=1, and K_1=K_2=K_3=6. Appendix B provides additional details regarding the inference procedure and the selection of the specification.

2.4. Measuring resilience as psychological loss

After estimating the dynamic finite mixture model, we derive individual-specific values of the parameters that govern individual differences in psychological responses to adverse events. We then construct individual measures of resilience, and examine how they correlate with variables that describe childhood circumstances.

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:

$$TPL_i(s) = -\sum_{s=t-1}^{+\infty}\left(H_{.s}(.,S_{.t}=s,\tilde{u}_{.t}=0;\rho_i,\mu_i)-H_{.s}(.,S_{.t}=0,\tilde{u}_{.t}=0;\rho_i,\mu_i)\right) \quad (9)$$

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:

$$TPL_i(s) = -\frac{\left(\mu_{i0}+\mu_{i1}\right)s}{1-\rho_i} \quad (10)$$

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:

$$\begin{aligned} p_{icl} &= \Pr(\rho_i=\rho_{lc},\mu_i=\mu_c \mid H_{i1},\dots H_{iT},S_i,x_i,H_{i0},w_i,\beta,\lambda) \\ &= \sum_{k=1}^{K_c}\Pr(\rho_i=\rho_{lc},\mu_i=\mu_c,\theta=\theta_{kc} \mid H_{i1},\dots H_{iT},S_i,x_i,H_{i0},w_i,\beta,\lambda) \\ &= \sum_{k=1}^{K_c}\frac{p_c\pi_{klc}\Pr(H_{i1},\dots H_{iT} \mid S_i,x_i,H_{i0},w_i,\rho_i=\rho_{lc},\mu_i=\mu_c,\theta=\theta_{kc},\beta,\lambda)}{\Pr(H_{i1},\dots H_{iT} \mid S_i,x_i,H_{i0},w_i,\beta,\lambda)} \end{aligned} \quad (11)$$

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

$$TPL_i^*(s) = \mathbb{E}\left(TPL_i(s) \mid H_{i1},\dots H_{iT},S_i,x_i,H_{i0},w_i,\beta,\lambda\right) = \sum_{c=1}^{C}\sum_{l=1}^{L_c}p_{icl}TPL_{lc}\left(s;\rho_{lc},\mu_c\right) \quad (12)$$

[14] Here, resilience is about 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.

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

$$TPL_{lc}(s;\rho_{lc},\mu_c) = -\frac{\left(\mu_{c0}+\mu_{c1}\right)s}{1-\rho_{lc}} \tag{13}$$

In a second step, we can estimate the extent to which childhood characteristics predict resilience.[15] In these regressions, *TPL* is standardised using the standard deviation of psychological health

2.5. Discussion

The above outlined modelling approach is similar to empirical methods from in the existing 'latent class' literature in economics and psychology, including economics studies that have modelled heterogeneity in the relationship between income and wellbeing (Clark et al., 2005; Brown et al., 2014) and psychology studies that have modelled heterogeneity in the dynamics of psychological health after a major life event (see, for example, Galatzer-Levy and Bonnano, 2012; Mancini et al., 2011; Galatzer-Levy et al., 2011; Galatzer-Levy et al., 2010; Kariuki et al., 2011; and Bonnano et al., 2012). However, our work differs from these studies in three main ways. First, we identify individual psychological response profiles that are common to a large set of commonly experienced major adverse life events; this strengthens the identification of resilient individuals and avoids restricting the sample to individuals affected by a single specific type of event (such as death of a spouse), potentially introducing sample selection bias. Our identification, based on the psychological response to ten commonly experienced life events, is also more general and wide-ranging than studies that have focused on the psychological response to particular natural disasters, technological shocks, and terrorist attacks.

Second, we do not presume *a priori* that individuals belong to only one latent class. Rather, we suppose that each class represents an 'ideal type' of profile defined by the same levels of $\{\rho_i, \mu_{i0}, \mu_{i1}\}$. However, if individuals are well-classified into the different classes (p_{ilc} is close to 1 or 0), then the class-specific measures of resilience and the individual-specific measure in (14) will provide similar results. If the classification is fuzzier, with many individuals having ex-post

[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.

probabilities p_{ilc} far from 0 and 1, then the individual-specific measure we identify is a more efficient tool for examining the correlations between resilience and childhood circumstances. The latter turns out to be clearly the case in our application.

Third, we control for unobserved fixed heterogeneity in the baseline and variance of psychological health. Therefore, our resilience measure is derived from a within-individual approach to adaptation, rather than population-level statistics based on cross-sectional variations in psychological health that mix individual levels of psychological health with the frequency of events and their impact on individuals. Because we use a vector of standardised events for the calculation of *TPL*, individual differences in resilience do not reflect variations in occurrences of adverse events. This clearly delineates two different targets for policy intervention and evaluation: on the one hand, individual resilience, and on the other, occurrences of adverse events.

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 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 2012, with each wave providing detailed information on a wide-range of economic, social, health and demographic information. The household response rates range from 87.0 percent in Wave 2 to 70.8 percent in Wave 11, while the household response rates for only those households responding in the previous wave range from 87.0 percent in Wave 2 to 96.4 percent in Wave 11 (Summerfield et al., 2012).

We use HILDA because it includes: 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 and 9) and a locus of control questionnaire (Waves 3, 4, 7 and 11); and respondents are asked retrospective questions about their childhood circumstances, including their measures of their socioeconomic and health. The retrospective questions on childhood and 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 information.

We focus on respondents who were aged 25 to 69 in their first survey. We began at age 25 because we wish to identify individuals' intrinsic resilience and its association with childhood circumstance, rather than the contemporaneous effects of family material and psychological support. For instance, heterogeneity in very young adults' psychological response to an adverse event (e.g. being fired or made redundant) may be driven by the level of direct support received from parents (e.g. financial, housing) rather than by differing levels of resilience. We also exclude those individuals observed for less than six consecutive periods, a sufficient time period to observe the full adaptation profile of most adverse 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 key psychological health and adverse event variables. Given that the adverse event questions are not included in Wave 1 of HILDA, this restriction implies that equation (1) is estimated using information from Waves 2-12. 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 5,557 individuals and 45,809 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 $I_{it}^1, \dots, I_{it}^K$ by a measurement function $\mathcal{M}$:

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

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 2.355) and the second component summarises physical health (eigenvalue equals 2.125). 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 51.0 and a standard deviation of 9.51. 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 37, and 5% of the observations have scores lower than 31.

3.3. Ten major adverse life events

As noted earlier, 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 how long ago.[17] The list has 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)".

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[16] Note that simultaneously estimating the measurement model and the latent class 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 the technical appendix).

[17] While respondents also 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 follow the bulk of the literature in aggregating these into yearly events.

Table 1 provides descriptive characteristics for each of these events, with 43% of respondents reporting at least one of them in the panel window. 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 16.8 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’ and then ‘death of a close friend’, which are reported in around 11 percent of the year-person observations. A major worsening of finances, and being fired or made redundant, are reported in around 3 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. Childhood and adulthood sample characteristics

Table 1 also shows the average of the contemporary (proximal) adulthood covariates used in our analyses. The average age of the sample is 49; 47 percent of observations are male; and 48 percent are employed full-time, with 2 percent being unemployed. Just under one-third (27 percent) have a university degree-level education, the log of annual household income is 11.00; 77 percent are married or cohabitating; and the average number of dependent children is 0.67. 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. One in ten of the observations in our sample report a current diagnosis of depression and/or anxiety; nearly 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.

In various waves of HILDA, the respondents are asked retrospective questions about their childhood circumstances, with the reference point being age 14. The questions relate to their family structure, broad socioeconomic characteristics, and their childhood health status. The variables we use to examine the extent to which childhood characteristics predict adulthood resilience are shown in Table 2. On average, respondents report having 2.9 siblings (the median is about 2, with a long tail); 8 percent immigrated to Australia before the age of 14; and about 1 percent had their mothers, and 6% their fathers, absent from the family household due to divorce. Similarly, by age 14, for 1 percent of respondents their mother had died, and for around 4 percent their father had died. Just under half of the respondents (47 percent) report that their mother was employed, and the statistics for fathers’ occupation show that our sample respondents come from a wide range of broad socioeconomic backgrounds. About 40 percent had a father working in managerial or professional occupations; and on the other end of the occupational scale, about 22 percent of fathers were machine operators, drivers and labourers. In terms of childhood health, the majority of respondents

(56 percent) report having been in excellent health at age 14, but just over 5% report having been in only fair or poor health.

Although we would prefer to have information that covers the entire of childhood, the measures do relate to the important teenage years and are likely easier for the adult respondent to recall than earlier childhood. Moreover, given the strong persistence in household socio-economic status (Aaronson and Mazumder, 2008) our measures (at age 14) will be highly correlated with early childhood circumstances.

4. Results

4.1. Psychological response to major adverse events

Our main results are presented in Table 3. 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 (0.193) 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 (-3.082), separation from spouse or partner (-2.345), injury or illness to self (-2.301), and being a victim of violent crime (-2.172). Interestingly, the second largest immediate decline in psychological health arises from a major worsening of financial situation, such as a bankruptcy (-2.577). In contrast, there is only a relatively small immediate response from having been fired or made redundant (-0.410). Moreover, the model reveals that many of these adverse events cannot be treated as shocks: the largest psychological anticipation responses occur before the actual event for separation from spouse or partner (-1.658) and death of spouse or child (-1.254). In contrast, the only events for which we find no significant evidence of anticipation effects are death of a close relative, death of a close friend, and being a victim of property crime.

Turning to our preferred specification (Columns 2-4 in Table 3) shown in Equation (2), aimed at better capturing heterogeneity in psychological response, we identify three distinct slope ‘classes’ of individuals, each describing about one-third of our sample (32.9%, 33.5% 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. In particular, the coefficients on the event variables are much larger for Class 3 than for Class 2, and to a lesser extent are higher for Class 2 than for Class 1. For instance, the immediate effect of a separation from spouse or partner equals -4.557 for Class 3, -0.969 for Class 2, and –0.362 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 (0.470) than for Classes 1 (0.086) and 3 (0.095). These estimates imply 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 53% and 29% 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 dynamic random-effect linear model estimate of 0.193, 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 coefficients in the different adverse events again are in line with expectations. For Class 3, the death of a spouse or child is not surprisingly the worst event that we measure, with an immediate standard deviation (-10.073) drop in psychological health. For a major financial worsening, separation from a spouse or partner, an own serious illness or injury, and physical assault, each is estimated to reduce psychological health by about a half-standard deviation in the short term. However, for individuals in Class 3 being fired or made redundant, or being a victim of property crime, are not significantly related to psychological loss. 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 (-2.417), being fired or made redundant (-1.564), and injury or illness to self (-1.377).

In contrast to these results the estimates, for Classes 1 and 2 are generally small and statistically insignificant. For Class 1, all but one coefficient is statistically insignificant; is implies small psychological responses to all major adverse events. For Class 2, the coefficients on psychological health are only significantly negative for death of a spouse or child (-1.296), separation from spouse or partner (-0.969), and own (-0.822) or family member (-0.419) injury or illness.[18]

In the second half of Table 3 we present the estimation results for the intercept α_{kc} and error variance parameters σ_{kc} that are specific to each of the 18 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.

[18] The control variable coefficients in our finite mixture model, shown in Appendix Table A2, are difficult to interpret because they are related to the probability of belonging to each of the three classes and the initial conditions variables. From the reduced-form results in Column 1, however, we see that this data displays familiar effects of control variables: males, younger individuals, higher income individuals, employed individuals, and couples with few children have better psychological health.

These estimates and the estimated autoregressive parameter ρ_{lc} fully characterise the 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 all of the six intercept parameters, and the estimated variance parameters (5.51, 3.02 and 2.57) are much lower than the raw variance of psychological health, which is normalised to equal 10. Because Class 1 individuals also have a low estimated autoregressive parameter, it represents the 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 2.22 for c=2 and k=3 to 8.76 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 (12.00 for c=3 and k=2; 8.6 for c=3 and k=6). 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

Figure 2 displays the extent of response heterogeneity by summarising the coefficients on the different intercepts and variances shown in Table 2. The left-side graph in Figure 2 shows 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 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). In Appendix Figure A1, we also provide the psychological response profiles by Class separately for each event. In terms of the SE, 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 not especially large – the immediate response for Class 3 is around 10 percent of a standard deviation of psychological health. However, Figure 3 presents the occurrence-weighted average response for the ten events, including 'death of a friend', 'injury and illness to a relative' and 'victim of property crime', which are relatively common but estimated to have small impacts on psychological health (see Appendix Figure A1).

Figure 4 further demonstrates the extent of heterogeneity in the total pyschological loss (TPL) associated with an SE (see equation (13) in Section 2). Approximately 5 percent of the sample is estimated to experience a loss totalled across all periods of around 0.03 units of standardised psychological health (corresponding to 3 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. Appendix Figure A2 presents the total pyschological loss associated with each event separately, similarly demonstrating the significant level of heterogeneity across individuals, but also demonstrating the significant variation across the different types of adverse events. For example, for 'death of a spouse or child' and 'death of a relative', the least resilient individuals experience a loss of around 135 percent and 6 percent of a standard deviation of psychological health, respectively.

4.3. Relationship between psychological resilience and adulthood characteristics

Table 4 shows the extent to which total psychological loss (TPL) following a SE is related to the probability of experiencing each of the ten adverse events and to some key demographic and socioeconomic characteristics in adulthood. To aid interpretation we split the predicted psychological loss distribution into terciles: tercile 1 are the most resilient with the smallest psychological loss, while the third tercile are the least resilient with the largest psychological loss. Looking at these adverse events, it is apparent that most are reasonably well balanced across the terciles, with no particularly large differences. This suggests that our modeling framework has controlled reasonably well for selection into these events.[19] For example, we can see that the more resilient individuals in the first tercile are nearly equally as likely to experience a significant death (of a spouse or partner; a friend; or a relative) as those in the second and third terciles. However, the least resilient in the third tercile are more likely to be fired or made redundant, have an injury or illness, and be a victim of physical violence, than those in the first and second terciles. Nonetheless, we do not find that those who experience the smallest psychological loss (first tercile) are also the least likely to experience each of the ten adverse events. Rather, those in the second tercile have the lowest likelihood of experiencing all of the ten events. This does not support the idea that people who are experience more events become more resilient, or that it is the weight of events that makes people less resilient. Moreover, these results tend to support resilience being is a fairly stable trait in adulthood.

The fairly even spacing of events over terciles of psychological loss also makes it unlikely that our methodology is driven by some kind of event intensity; for example that the event itself is more dramatic for some terciles (e.g. like a bigger financial loss, or a more serious illness or accident). If that were the case, then we should see more pronounced differences in event frequencies, particularly for those events that are likely to be more intense that others (e.g. death of spouse). Instead, we find little heterogeneity in the frequency of events, suggesting that what we identify is more the reaction to the same stimuli than to different stimuli.

While the average age for each tercile is around 50, there are fewer males in the third tercile than females. This suggests that females suffer a larger psychological loss from major adverse events than males (see Boardman et al., 2008, for a discussion of gender differences in resilience). The least resilient in the third tercile also are less likely to be employed full-time, although there is little difference by highest education level in the psychological response to adverse events across the terciles. Similarly, the difference in household income between terciles is small, but it is a little lower for the third tercile, possibly reflecting lower full-time employment than for individuals in the first and second terciles.

If our measure of psychological resilience is capturing valid variation, then we would expect it to be strongly correlated with the probability of having a mental health condition. Bases on the information collected in the HILDA survey, the bottom section of Table 4 shows the relationship

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[19] This shows the benefit of working with a large set of events: we minimize the risk of biasing our estimates by selection into events on event-individual-specific time-varying unobservables because the latter are likely to be independent.

between the psychological loss terciles and the likelihood of: (a) currently being diagnosed with depression or anxiety; (b) currently taking medication for depression and anxiety; and (c) having seen a psychiatrist or psychologist in the past year. We see the very large differences, with those in the third tercile (least resilient) having around a 7-fold greater likelihood (17.1 percent) of currently being diagnosed with depression or anxiety than those in the first tercile (2.4 percent), and nearly double that of the second tercile (9.2 percent). These differences also are clearly reflected in the taking of prescription medication, and are greatest for having seen a medical specialist in the past year (8.1 percent for the third tercile compared to 0.9 percent for the first tercile). These substantive differences indicate that resilience (as we have measured it) is an important construct that is related to large costs to the public health system.

4.4. Is resilience distinct from cognitive ability and personality?

Next we investigate the correlation between estimated psychological resilience and measures of cognitive ability and personality collected in HILDA (details of how these measures are derived can be found in Appendix C). Table 5 presents the estimates from a regression of our standardised total psychological loss measure on these traits. Studies in the psychology literature have identified high intelligence as being predictive of resilience in the face of adversity (Martinez-Torteya et al., 2009). Consistent with this literature, we find that cognitive ability is positively and significantly associated with experiencing a smaller psychological loss from major adverse events (i.e. being more resilient). However, the magnitude of this relationship is small, with a one-standard deviation increase in cognitive ability associated with only a 0.2 percent of a standard deviation reduction in the total psychological loss to a standardised event.

A number of economic studies have found that having an external locus of control is associated with lower human capital and poorer labour market outcomes (see, for example, Cebi, 2007; Caliendo et al., 2015). We also find that an external locus of control is positively and significantly related to having lower psychological resilience following an adverse event. This seems reasonable, because a higher internal locus of control is thought to characterise individuals who are more self-controlled. Further, having a neurotic personality (partly defined as having a lack of emotional stability) is significantly associated with lower resilience (larger psychological loss). Smaller but still statistically significant factors are extraversion (increasing with resilience) and openness (decreasing with resilience). Together, these intuitive correlations indicate that our resilience measure correctly captures differential responses to adverse events. However, given the moderate magnitude of these correlations and an R-squared value of only 0.12, the results suggest that resilience as estimated by our model is an independent construct from cognitive ability and personality.

4.5. Childhood predictors of adulthood psychological resilience

Our final analysis explores the relationship between childhood circumstances and resilience in adulthood. As mentioned earlier, there exists debate about whether resilience is a fixed trait or a dynamic process. It is likely a combination of both – similar to the within-individual variation in subjective wellbeing over time – but the relative importance of the stable and time-varying components are unknown.[20] Regardless of whether psychological resilience is a fairly fixed trait (in adulthood) or a dynamic process that moves in response to different types of life events, it is of interest to determine the extent to which childhood circumstances can predict resilience during adulthood. Weak associations would suggest that we have incorrectly identified the relevant childhood circumstances and/or that the stable component of resilience is small.

Studies in psychology have found that low resilience is correlated with many factors in childhood, including poverty, parental mental illness, poor parenting, maltreatment, neglect, abuse, and the experience of violence (Luttar et al., 2000). Seery et al. (2010) find that some (mild) adverse experiences may foster resilience, giving one an advantage in terms of mental health and wellbeing. Some factors that have been found to be positively correlated with resilience are: a positive and supportive relationship between caregiver and child; competent parenting; good mental health of caregiver; and, in terms of child characteristics, an engaging temperament and higher cognitive ability (Martinez-Torteya et al., 2009).[21]

As discussed in Section 3, the adult respondents in HILDA were asked to recall some aspects of their childhood, including their family composition, father's occupational status and their health as a child.[22] Table 6 presents the results from models that use this retrospective data. First using the full sample is a simple linear regression of the total psychological loss to a standardised event on childhood characteristics. Second, we present estimates separately by gender. Overall, our model has some explanatory power in predicting adulthood resilience, but much remains unexplained with an R-squared of 0.035. The coefficient estimates suggest that a greater number of

[20] In terms of locus of control, and the Big-5 personality traits, Cobb-Clark and Schurer (2012, 2013) find evidence of high stability in adulthood, concluding that, "Intra-individual changes are generally unrelated to adverse life events and are not economically meaningful."

[21] Afifi and MacMillan (2011) review of psychiatry literature on resilience of maltreated children and the factors that provide protection. They note that, "although comparability across studies is limited, family-level factors of stable family environment and supportive relationships appear to be consistently linked with resilience across studies. There was also evidence for some individual-level factors, such as personality traits, although proxies of intellect were not as strongly related to resilience following child maltreatment".

[22] We are unaware of any longitudinal survey that contains all of the information (i.e. life events) and properties (i.e. a long annual panel) that we need to estimate our main model, and collects more detailed information on specific childhood adversities. Surveys such as the UK National Child Development Study (NCDS), the US National Longitudinal Survey of Youth (NLSY) and the US National Longitudinal Study of Adolescent to Adult Health (Add Health) have asked respondents to recall adversities from their childhood, but the long period between surveys would not allow for the identification of psychological loss (resilience) as we have been able to do; we would not observe the timing of life events very well, and anticipation and full adaptation to life events likely would be unobserved between survey waves.

siblings, having a working mother, and father having died, each are associated with greater psychological loss (or lower resilience) from a standardised adverse event, but these are only significant at the 10 percent level. In particular, losing your father in early life is associated with a 0.9 percent of a standard deviation increase in total psychological loss. We also find some evidence of a socioeconomic gradient, as defined by broad occupational class of father: having a father who worked as a machinery operator/driver or a labourer is associated with a 0.6 and 0.8 percent of a standard deviation greater psychological loss, respectively, compared to the base level for managers.

By far the strongest predictor of resilience in adulthood that we identify is childhood health, and it follows a monotonic relationship. In comparison to a childhood of 'excellent' health, having only 'very good' health increases psychological loss following a standardised event in adulthood by 0.7 percent of a standard deviation. This increases to 1.4 percent, 2.3 percent, and 3.0 percent, respectively, for 'good', 'fair', and 'poor' health. If we additionally include controls for cognitive ability and personality traits in this model, the strong relationship between childhood health and adult resilience remains. However, we are cautious about over emphasising this finding for two reasons. First, we cannot rule out that childhood health itself might partially be reflecting early life resilience. Second, it is possible that part of the strong relationship is explained by retrospective bias in the reporting of childhood health. It is possible that certain adverse events in adulthood may 'change' the way in which an adult recollects their childhood circumstances., However, to the extent that childhood health is capturing true differences between respondents, then the finding of a strong childhood gradient in adult resilience provides additional support for the case of public investment in health in the early years of life (see Case et al., 2005).

The results by gender are similar to those in column (1), with one notable difference being the estimated coefficients for having a working mother. For men, having a working mother during childhood is associated with a 0.9 percent of a standard deviation increase in total psychological loss (a reduction in resilience); for women the coefficient is near zero and statistically insignificant. Using British data, Powdthavee (2014) found that maternal employment status was an important predictor of resilience to unemployment shocks among young adults, but in contrast to our results, his association was stronger for women.

6. Conclusion

It is important to understand who in the population is resilient, and how the distribution of psychological resilience differs across the type of adverse life events that individuals commonly experience. Examples are death of a spouse or a close friend, divorce, redundancy, bankruptcy and crime victimisation. This knowledge provides policy-makers with information that can be used to better direct resources to individuals and communities most at risk (Clark, 2016). In Graham and Oswald's (2010) theoretical framework building hedonic capital increases resilience, which smooths psychological responses to adverse events, thus reducing mental illness in society. In Cuhna and Heckman's (2009) child development model they highlight the benefits of developing resilience, particularly for disadvantaged children.

Particularly in psychology, a large literature focuses on childhood resilience, and how many children who grow up in an environment of disadvantage and adversity, overcome this difficult start to life. A second body of research describes and classify the psychological responses of adults to a wide range of events, much of the research concentrating on bereavement and on different types of natural disasters. However, many of these studies focus on only one type of event, and the analysis often is conducted using small case-study samples, making any inference about the population distribution of resilience difficult. In contrast, there are still very few economics studies that have focused on psychological resilience, despite the substantial economic costs of mental illness for individuals, families, communities and workplaces.

In this paper, we have applied an empirical methodology that builds upon recent studies, mostly in psychology (see Bonanno et al., 2010; Mancini et al., 2011) and economics (Clark et al., 2005; Brown et al., 2014), that use latent class modelling techniques to better capture and inform on the extent of heterogeneity in the psychological or subjective wellbeing response to adverse events. In particular, we fitted a flexible mixed linear dynamic model of psychological health which allows for individual heterogeneity in anticipation, contemporaneous impact, and adaptation speed, to 11 waves of nationally representative panel data. The model takes into account the initial conditions problem, and the fact that individuals are not randomly allocated to experience adverse events. Rather than focusing on only one type of event, we analyse detailed panel data allowing us to jointly consider ten major adverse events. We therefore can make broader generalisations about the distribution of resilience in the population than have most previous studies. These adverse events are important to examine because they are commonly experienced: some 42% of our panel respondents report a major adverse event within the 11-year window of observation. We then relate our estimated measure of psychological resilience back to childhood, attempting to identify the extent to which childhood socioeconomic circumstances predict resilience in adulthood. While we gain important insights from this analysis, given the complexities involved and data limitations, it does not allow us to make any causal claims that improving a specific aspect of childhood would improve resilience in adulthood.

We find substantial heterogeneity in the psychological response to major adverse life events: around one-third of the sample are little affected by such events, while one-third experience substantive declines in their psychological health. Overall, we identify 18 latent classes, each with a different distribution of total psychological loss after a standardised event (see Figure 2). The dynamic finite mixture model also predicts large differences between the most resilient and least resilient individuals in our sample. Notably, we find some support for our measure of resilience in the strength of its relationship with experienced mental health conditions: our measure of psychological resilience is strongly correlated with being diagnosed with depression or anxiety, taking medication for depression or anxiety, and having seen a psychiatrist or psychologist in the last year. In particular, those who are estimated to be the least resilient are seven times more likely to be currently diagnosed with depression or anxiety than those estimated to be the most resilient. Further, we show that our resilience measure captures a different construct to cognitive ability, locus of control, and the Big-5 personality traits. We find that resilience is significantly correlated with these measures, in plausible directions, but predict little of the variation in resilience.

Finally, we find some evidence that broad socioeconomic circumstances in childhood are predictive of psychological resilience in adulthood, although there is much left unexplained by the variables that we have available. In particular, while we find some evidence of a childhood SES gradient in adulthood resilience, with children who had a father working in unskilled or low skilled occupations predicted to have lower adult resilience than children of professionals and managers, the size of these differences is not large. More notably, we find that childhood health status is the strongest predictor of future resilience, with poor childhood health being associated with significantly lower psychological resilience. This result is supportive of a wider literature in economics that emphasises the importance of tackling early life inequalities in health, given their long-term socioeconomic consequences (see, for example, Case et al., 2005; Goodman et al., 2011).

While the mixed linear dynamic model of psychological health we apply is flexible, and we think provides some advancement in the literature on resilience by more fully capturing the substantial heterogeneity in the psychological response to life events, it is not without its identifying assumptions. In particular, we do not explicitly model the probability of occurrence of events and we can only control for self-selection on time-invariant characteristics. We also have to assume that the resilience parameters are independent from the occurrence of events, and thus cannot allow for resilience to have a dynamic component.

We believe that better understanding the population distribution of resilience, which can smooth psychological responses to commonly experienced adverse events, and identifying the types of individuals who are more or less likely to be resilient, are important topics for economists. By reviewing in some detail the mainly psychological literature, drawing attention to the complementary research undertaken by economists on hedonic adaptation to life events, and providing new evidence on the extent of heterogeneity in psychological responses to common adverse life events, we hope that this paper will help promote further research on resilience by economists.

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Figure 1: Empirical Distribution of Psychological Health

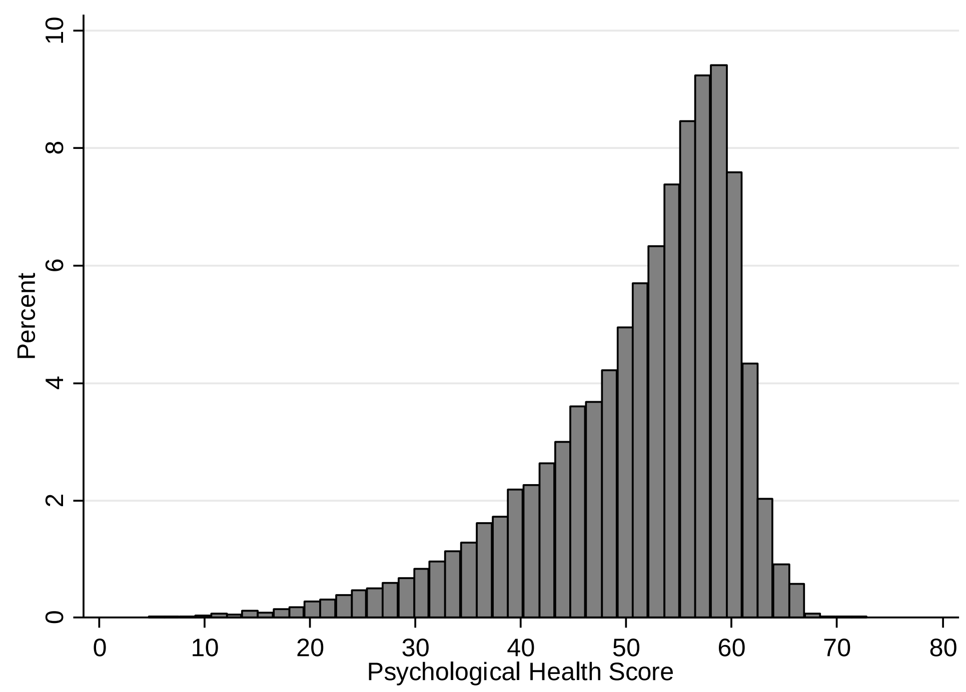


Table 1: Descriptive Statistics for Adulthood Variables

	Mean	Std. Dev.	Min	Max
Life Events				
Major worsening in financial situation	0.029	0.169	0	1
Fired or made redundant by an employer	0.026	0.159	0	1
Separated from spouse or long-term partner	0.027	0.161	0	1
Death of spouse or child	0.006	0.079	0	1
Death of other close relative / family member	0.112	0.316	0	1
Death of a close friend	0.108	0.311	0	1
Serious injury or illness to self	0.080	0.271	0	1
Serious injury or illness to a close relative	0.168	0.374	0	1
Victim of physical violence	0.009	0.097	0	1
Victim of a property crime	0.040	0.197	0	1
Contemporary characteristics				
Age	49.21	12.14	25	80
Male	0.467	0.499	0	1
Employed full-time	0.476	0.499	0	1
Employed part-time	0.216	0.411	0	1
Unemployed	0.018	0.135	0	1
Out of the labour force	0.290	0.454	0	1
Highest qualification: University degree	0.269	0.444	0	1
Highest qualification: Vocational diploma	0.316	0.465	0	1
Highest qualification: High school graduate	0.108	0.310	0	1
Highest qualification: High school dropout	0.307	0.461	0	1
Log household income	11.00	0.669	7.188	14.29
Married or cohabiting	0.774	0.419	0	1
Divorced or separated	0.109	0.312	0	1
Single and never married	0.117	0.322	0	1
Number of children	0.669	1.039	0	9
Cognitive ability and personality traits				
Cognitive test score (std)	0.091	0.956	-3.482	3.204
External locus of control (std)	-0.032	0.942	-1.831	3.622
Extraversion (std)	-0.056	1.014	-3.206	2.393
Agreeableness (std)	0.057	0.936	-4.619	1.744
Conscientiousness (std)	0.138	0.964	-3.938	1.865
Neuroticism (std)	0.045	0.972	-3.727	1.660
Openness (std)	0.032	0.963	-2.975	2.621
Clinical measures of psychological health				
Current diagnosed depression / anxiety	0.096	0.294	0	1
Take depression/anxiety prescription meds	0.047	0.211	0	1
Seen psychiatrist/psychologist in past year	0.055	0.227	0	1

Notes: Sample size equals: 5,557 individuals (45,809 individual-waves) for life events and contemporary characteristics; 5,552 individuals for cognitive ability and traits; 4,506 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: Descriptive Statistics for Childhood Variables

	Mean	**Std. Dev.**	**Min**	**Max**
Number of siblings	2.853	2.119	0	18
Immigrate ≤ age 14	0.077	0.266	0	1
Parents divorced: Mother absent	0.012	0.108	0	1
Parents divorced: Father absent	0.060	0.237	0	1
Mother had died	0.011	0.103	0	1
Father had died	0.035	0.184	0	1
Lived without both parents	0.022	0.147	0	1
Mother employed at age 14	0.471	0.499	0	1
Father occupation: Manager	0.258	0.437	0	1
Father occupation: Professional	0.142	0.349	0	1
Father occupation: Technician / trade	0.240	0.427	0	1
Father occupation: Community / personal service	0.035	0.184	0	1
Father occupation: Clerical / administration	0.063	0.242	0	1
Father occupation: Sales	0.044	0.205	0	1
Father occupation: Machinery operator / driver	0.110	0.313	0	1
Father occupation: Labourer	0.109	0.311	0	1
General health: Excellent	0.563	0.496	0	1
General health: Very good	0.243	0.429	0	1
General health: Good	0.104	0.306	0	1
General health: Fair	0.037	0.190	0	1
General health: Poor	0.014	0.119	0	1

Notes: Sample size equals N=5,266 individuals. All of these measures are based on retrospective accounts of childhood from adult HILDA respondents.

Table 3: Dynamic Random Effect and Dynamic Finite Mixture Models of Psychological Health

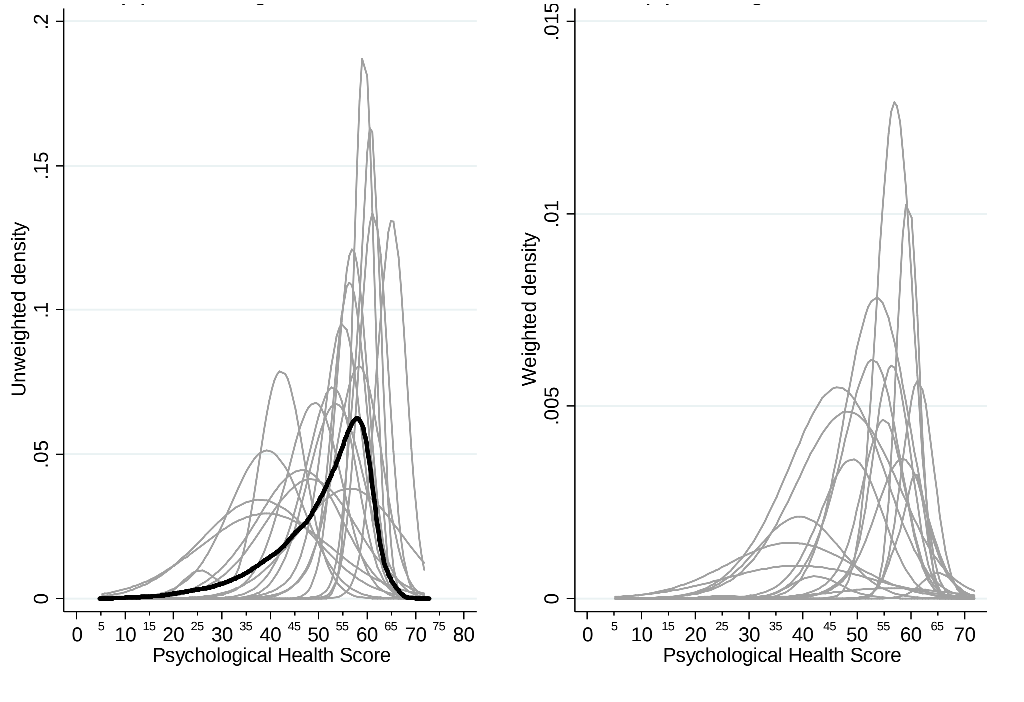
		Dynamic RE model	Dynamic Finite Mixture Model		
			Finite Mixture Parameters		
			c=1	c=2	c=3
		Lagged Psychological Health Parameter (ρ_i)			
Psychological health in *t*-1		0.193***	0.086***	0.470***	0.095***
		(0.005)	(0.011)	(0.012)	(0.012)
		Immediate (μ_{0i}) and Anticipation (μ_{1i}) Parameters			
Major financial worsening	*t*	-2.577***	-0.242	-0.181	-5.709***
		(0.190)	(0.333)	(0.457)	(0.664)
	t+1	-0.776***	-0.479	-0.670	0.092
		(0.190)	(0.295)	(0.492)	(0.489)
Fired or made redundant	*t*	-0.410**	0.124	-0.630	-0.733
		(0.196)	(0.269)	(0.408)	(0.621)
	t+1	-0.892***	-0.196	0.504	-1.564***
		(0.196)	(0.275)	(0.372)	(0.542)
Separation from spouse	*t*	-2.345***	-0.362	-0.969*	-4.557***
		(0.205)	(0.315)	(0.503)	(0.659)
	t+1	-1.658***	0.095	-1.016*	-2.417***
		(0.198)	(0.324)	(0.526)	(0.641)
Death of spouse or child	*t*	-3.082***	-0.649	-1.296**	-10.073***
		(0.409)	(0.611)	(0.616)	(1.296)
	t+1	-1.254***	-0.810	0.278	-2.117
		(0.398)	(1.015)	(0.634)	(1.318)
Death of close relative	*t*	-0.386***	-0.128	-0.077	-0.791***
		(0.096)	(0.121)	(0.145)	(0.266)
	t+1	-0.058	-0.104	-0.205	0.228
		(0.094)	(0.114)	(0.147)	(0.233)
Death of close friend	*t*	-0.230**	0.074	-0.253*	-0.577**
		(0.103)	(0.117)	(0.151)	(0.255)
	t+1	-0.143	-0.109	-0.124	-0.112
		(0.101)	(0.113)	(0.153)	(0.246)
Injury or illness to self	*t*	-2.301***	-0.159	-0.822**	-5.106***
		(0.117)	(0.179)	(0.346)	(0.430)
	t+1	-0.808***	0.150	-0.527**	-1.377***
		(0.115)	(0.163)	(0.236)	(0.317)
Injury or illness to relative	*t*	-0.711***	-0.127	-0.419***	-1.148***
		(0.084)	(0.100)	(0.145)	(0.230)
	t+1	-0.214**	-0.196*	-0.085	-0.201
		(0.084)	(0.103)	(0.140)	(0.218)
Victim of physical violence	t	-2.172***	-0.386	-0.150	-4.051***
		(0.328)	(0.459)	(0.608)	(1.535)
	t+1	-0.855***	-0.633	0.354	0.222
		(0.332)	(0.462)	(0.599)	(0.952)
Victim of property crime	*t*	-0.387**	-0.212	-0.181	0.060
		(0.152)	(0.189)	(0.261)	(0.375)
	t+1	-0.241	-0.014	-0.480*	-0.381
		(0.158)	(0.215)	(0.284)	(0.411)

Table 3: (Continued)

	DRE	Finite Mixture Parameters c=1	c=2	c=3
		Intercept (δ_i) and Error Variance (σ_i) Parameters		
k=1, probability weight p_{1c}	-	0.7%	1.9%	4.8%
Intercept		35.780***	13.310***	32.665***
		(1.519)	(1.142)	(1.168)
Variance		9.669***	1.423***	3.508***
		(0.662)	(0.096)	(0.146)
k=2, probability weight p_{2c}	-	11.6%	4.3%	3.0%
Intercept		31.917***	4.651***	23.681***
		(1.060)	(1.076)	(1.246)
Variance		5.511***	8.756***	12.001***
		(0.102)	(0.259)	(0.371)
k=3, probability weight p_{3c}	-	10.5%	5.5%	4.4%
Intercept		34.161***	11.924***	35.907***
		(1.064)	(1.118)	(1.174)
Variance		3.016***	2.225***	4.137***
		(0.061)	(0.069)	(0.139)
k=4, probability weight p_{3c}	-	5.4%	8.5%	5.4%
Intercept		37.708***	10.546***	28.975***
		(1.078)	(1.099)	(1.144)
Variance		2.565***	3.560***	5.025***
		(0.061)	(0.093)	(0.196)
k=5, probability weight p_{3c}	-	0.5%	0.7%	4.2%
Intercept		35.622***	7.176***	23.008***
		(1.087)	(1.075)	(1.145)
Variance		1.830***	3.072***	6.857***
		(0.055)	(0.266)	(0.236)
k=6, probability weight p_{3c}	-	0.5%	12.5%	11.8%
Intercept		41.323***	8.922***	29.662***
		(1.096)	(1.070)	(1.143)
Variance		2.849***	6.037***	8.607***
		(0.177)	(0.115)	(0.138)

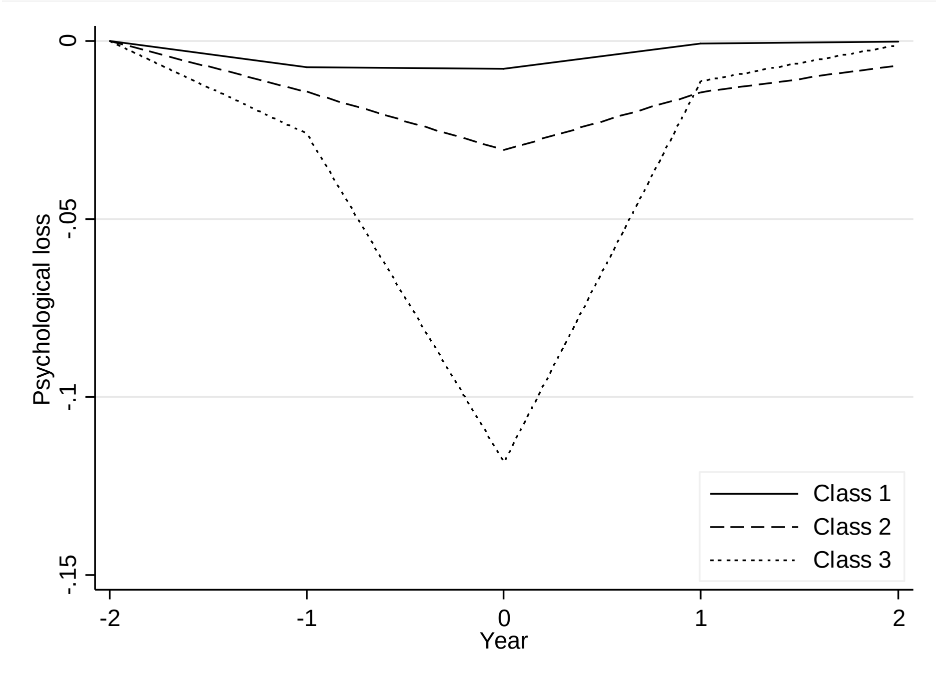
Notes: Column 1 reports results from a dynamic random effects model, where coefficients on lagged psychological health and life events are homogenous. Columns 2-4 report the estimated coefficients of the dynamic finite mixture model for classes 1 to 3 respectively. The upper panel of Table 3 reports the coefficients on lagged psychological health, and contemporaneous and future life events. The lower panel of Table 3 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.

Figure 2: Empirical Density and Predicted Class Specific Densities



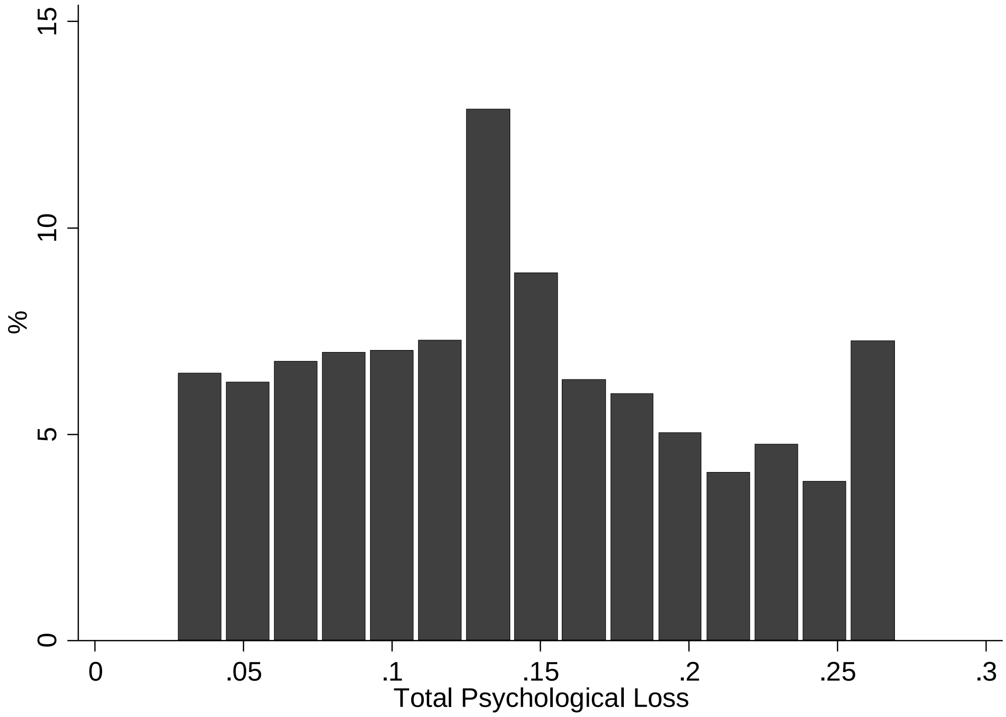
Notes: Black thick line: empirical distribution of psychological health (non-parametric fit); grey lines: unconditional class-specific distributions of psychological health simulated with the dynamic finite mixture model, weighted by the probabilities π_{kc} in the right panel, and unweighted in the 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 Total Pyschological Loss (TPL) to a Standardised Event (SE)



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

Table 4: Descriptive Statistics of Selected Adulthood Characteristics by Terciles of Total Psychological Loss (TPL) to a Standardised Event (SE)

	Terciles		
	1st	**2nd**	**3rd**
Adverse Events			
Major financial worsening	2.2%	1.9%	4.2%
Fired or made redundant	2.3%	2.1%	3.1%
Separation from spouse	2.2%	1.7%	4.0%
Death of spouse or child	0.5%	0.4%	0.7%
Death of close relative	10.5%	10.6%	11.3%
Death of close friend	10.8%	9.6%	10.5%
Injury or illness to self	6.3%	5.9%	10.3%
Injury or illness to relative	16.0%	15.3%	18.3%
Victim of physical violence	0.7%	0.5%	1.4%
Victim of property crime	3.7%	3.7%	4.8%
Basic Characteristics			
Age	50.25	49.11	48.03
Male	53.1%	47.1%	40.2%
Employed full-time	51.5%	48.0%	44.5%
University degree	28.0%	26.9%	26.6%
Vocational diploma	32.6%	30.6%	31.5%
High school graduate	11.2%	10.2%	10.9%
Log household income	11.03	11.02	10.94
Clinical psychological health			
Current diagnosed depression / anxiety	2.4%	9.2%	17.1%
Take depression/anxiety prescription meds	0.9%	5.1%	8.1%
Seen psychiatrist/psychologist in past year	1.7%	4.3%	10.3%

Notes: Terciles of total psychological loss from a standardised event defined using the estimated 33rd and 66th centiles. Sample size equals 5,557 individuals (45,809 individual-waves) for adverse events and basic characteristics, and 4,506 individuals for clinical outcomes.

Table 5: Linear Regression of Total Psychological Loss (TPL) to a Standardised Event (SE) on Personality Traits and Cognitive Ability

External Locus of Control	0.013***
	(0.001)
Extraversion	-0.003***
	(0.001)
Agreeableness	0.000
	(0.001)
Conscientiousness	-0.002*
	(0.001)
Neroticism	-0.011***
	(0.001)
Openness	0.003***
	(0.001)
Cognitive test score	-0.002**
	(0.001)
R-squared	0.121
Sample Size	5552

Notes: Figures are coefficient estimates from an OLS regression. Dependent variable is the total psychological loss in response to a standardised event, and has been standardised by the standard deviation in psychological health. The personality variables, and cognitive test score are all standardised to have standard deviation equal to one. Gender, age and age squared are also included as covariates in the regression model. Robust standard errors are shown in parentheses. *, ** and *** denote statistical significance at the 0.10, 0.05 and 0.01 levels, respectively.

Table 6: Linear Regression of Total Psychological Loss (TPL) to a Standarised Event (SE) on Childhood Circumstances

	All	Male	Female
Male	-0.014***	-	-
	(0.002)		
Age in years	0.002***	0.002***	0.001
	(0.001)	(0.001)	(0.001)
Age squared / 100	-0.002***	-0.003***	-0.002**
	(0.001)	(0.001)	(0.001)
Number of siblings	0.001*	0.001*	0.001
	(0.000)	(0.001)	(0.001)
Immigrate ≤ age 14	-0.003	-0.005	-0.001
	(0.004)	(0.005)	(0.005)
Parents divorced: mother absent	0.003	0.008	-0.004
	(0.008)	(0.011)	(0.012)
Parents divorced: father absent	0.003	-0.008	0.010*
	(0.004)	(0.006)	(0.005)
Mother has died	-0.004	-0.006	-0.001
	(0.009)	(0.014)	(0.012)
Father had died	0.009*	0.007	0.011
	(0.005)	(0.007)	(0.007)
Lived without both parents	0.002	0.008	-0.006
	(0.006)	(0.009)	(0.009)
Mother employed at age 14	0.004*	0.009***	-0.000
	(0.002)	(0.003)	(0.003)
Father occupation: Professional	0.001	0.006	-0.004
	(0.003)	(0.005)	(0.004)
Father occupation: Technician / trade	0.003	0.003	0.002
	(0.003)	(0.004)	(0.004)
Father occupation: Community / personal service	0.002	0.003	0.002
	(0.005)	(0.008)	(0.007)
Father occupation: Clerical & administration	-0.005	-0.000	-0.009*
	(0.004)	(0.006)	(0.005)
Father occupation: Sales	0.003	-0.002	0.007
	(0.005)	(0.007)	(0.007)
Father occupation: Machinery operator / driver	0.006*	0.010**	0.003
	(0.003)	(0.005)	(0.005)
Father occupation: Labourer	0.008**	0.006	0.009*
	(0.003)	(0.005)	(0.005)
General health: Very good	0.007***	0.008**	0.007**
	(0.002)	(0.003)	(0.003)
General health: Good	0.014***	0.018***	0.012***
	(0.003)	(0.005)	(0.004)
General health: Fair	0.023***	0.024***	0.023***
	(0.004)	(0.007)	(0.006)
General health: Poor	0.030***	0.032**	0.029***
	(0.008)	(0.015)	(0.010)
R-squared	0.035	0.030	0.024
Sample Size	5266	2460	2806

Notes: Figures are coefficient estimates from OLS regressions. Dependent variable is the total psychological loss in response to a standardised event. It has been standardised by the standard deviation in mental health. Omitted categories are lived with both parents, manager and excellent health. A dummy variable for 204 missing observations on general health is also included as a covariate in the regression model. There are 291 fewer individuals in this analysis due to missing information on childhood circumstances. Robust sstandard errors are shown in parentheses. *, ** and *** denote statistical significance at the 0.10, 0.05 and 0.01 levels, respectively.

Appendices to go online

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	0.179	-0.090
Physical role functioning	0.283	-0.106
Bodily pain	0.327	-0.067
General health perceptions	0.489	0.059
Vitality	0.701	0.279
Social functioning	0.659	0.236
Emotional role functioning	0.575	0.155
Mental health	0.800	0.431
Correlation of the MHC with life satisfaction	0.479***	
Observations	25,085 individuals observed at inclusion	

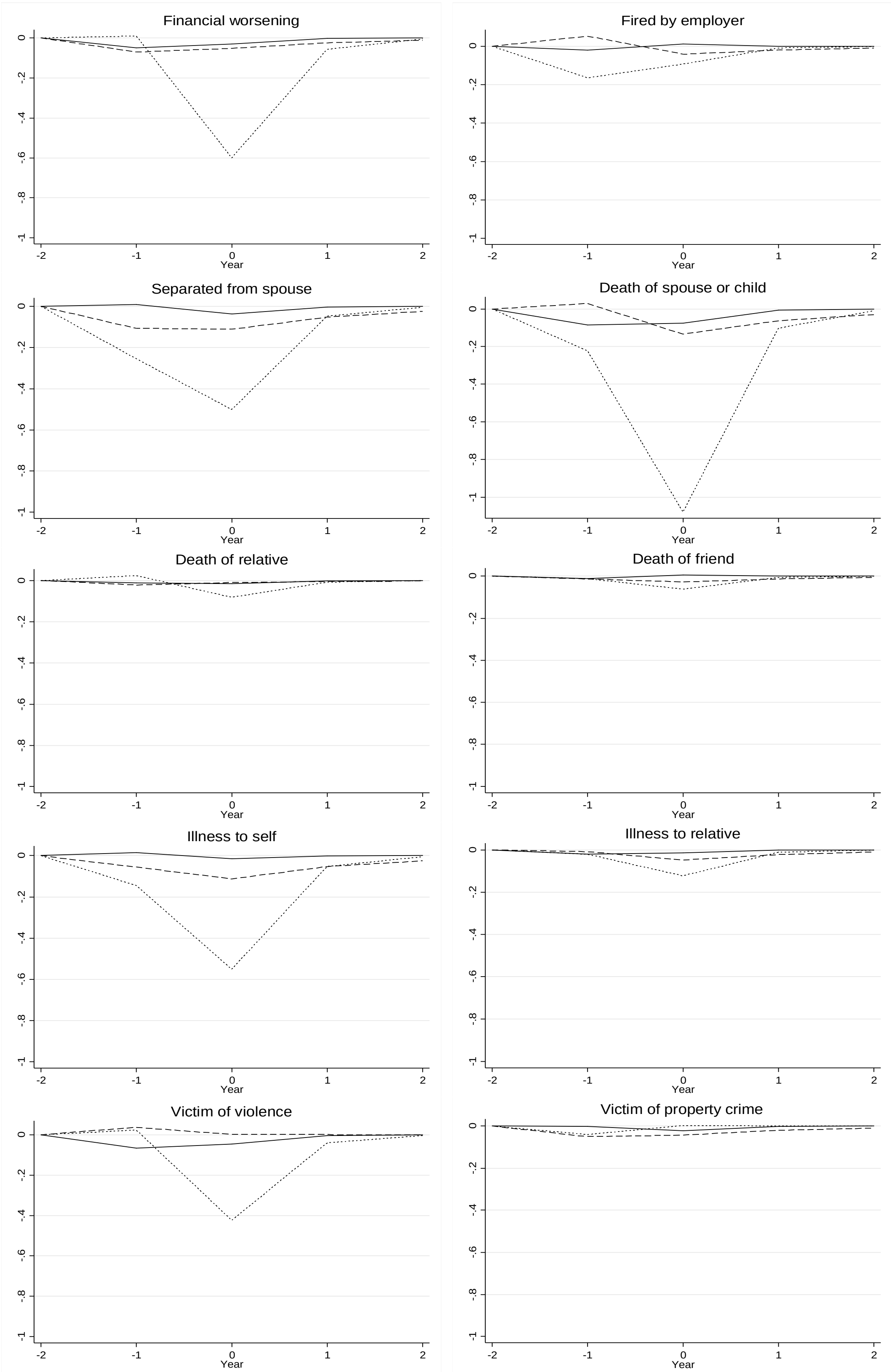
Notes: results from a factor analysis of the eight domain-specific scales of the SF-36, with a two-factor solution obtained after varimax rotation (mental health and physiological health). The factor loadings are the estimated coefficients of a ‘regression’ of the domain-specific scale on the two factors. 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	**Dynamic Finite Mixture Model**
Log Household Income	0.180**	0.071
	(0.087)	(0.082)
Age/10	-0.221	0.502
	(0.529)	(0.429)
$(\text{Age}/10)^2$	0.092***	0.017
	(0.031)	(0.024)
Male	0.065	-0.262***
	(0.120)	(0.077)
Employed: Full-time	0.133	-0.548***
	(0.145)	(0.160)
Employed: Part-time	0.578***	-0.089
	(0.131)	(0.141)
Unemployed	0.003	-0.318
	(0.257)	(0.325)
University degree	0.107	0.085
	(0.143)	(0.089)
Certif./Dip. Degree	0.093	0.247***
	(0.128)	(0.088)
12 years of schooling	-0.059	-0.004
	(0.178)	(0.111)
Married or cohabiting	0.586**	0.366
	(0.254)	(0.281)
Divorced or separated	0.321	0.551
	(0.317)	(0.386)
Number of children	-0.210***	-0.165***
	(0.062)	(0.062)
Other control variables	Year dummies Initial conditions	Year dummies Initial conditions

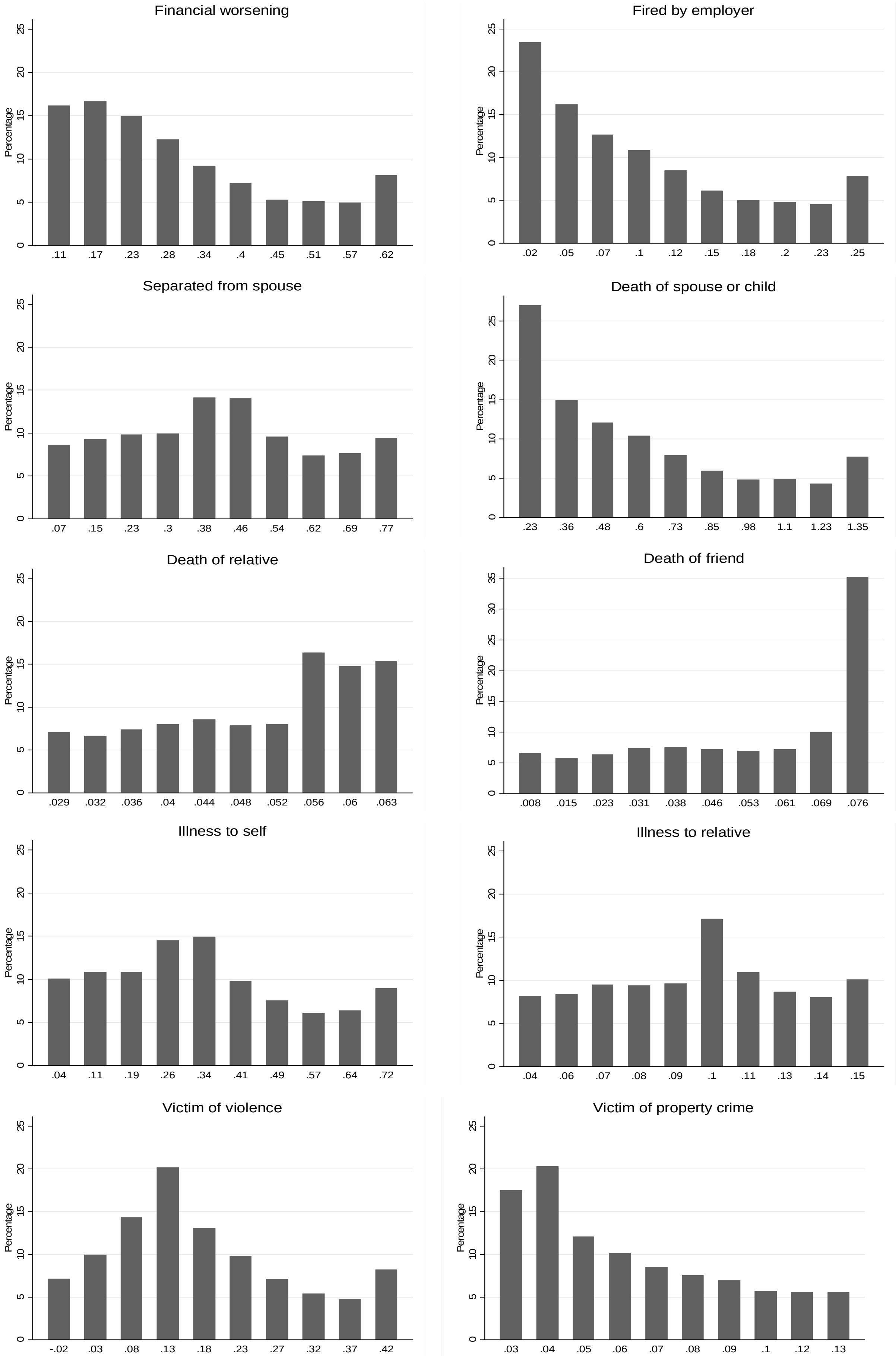
Notes: Estimation results of the Dynamic random Effect and the Dynamic Finite Mixture Models for the sociodemographic control variables. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Omitted categories are: female, not active, less than grade 12 schooling, and single.

Figure A1: Heterogeneity in the Psychological Response Profiles by 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 A2: Heterogeneity in the Total Pyschological Loss by Life Event



Notes: Y-axis represents percentage in sample. X-axis provides bin midpoints, which represent total standardised psychological loss.

Appendix B: Technical Appendix

Estimation procedure

For given values of C, K_c and L_c, the individual likelihood is a discrete mixture:

$$\Pr(H_{i1},\ldots H_{iT} \mid S_i, x_i, H_{i0}, w_i, \beta, \lambda) \propto$$
$$\sum_{c=1}^{C}\sum_{k=1}^{K_c}\sum_{l=1}^{L_c}\underbrace{p_c\pi_{klc}}_{p_{klc}}\left[\prod_{t=1}^{T}\phi\left(\frac{H_{it}-\rho_{lc}H_{it-1}-\beta' x_{it}-\mu_{0c}' S_{it}-\mu_{1c}' S_{it+1}-\lambda' w_i-\alpha_{kc}}{\exp(\sigma_{kc}')}\right)\right] \tag{B1}$$

Maximising directly the corresponding log-likelihood 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 Expected-Maximisation (EM) algorithm originally proposed by Dempster and Laird (1977).

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 (B1) to compute the posterior probabilities

$$\begin{aligned} p_{iklc} &= \Pr(\rho_i = \rho_{lc}, \mu_i = \mu_c, \theta = \theta_{kc} \mid H_{i1},\ldots H_{iT}, S_i, x_i, H_{i0}, w_i, \beta, \lambda) \\ &= \Pr(\rho_i = \rho_{lc}, \mu_i = \mu_c, \theta = \theta_{kc} \mid H_{i1},\ldots H_{iT}, S_i, x_i, H_{i0}, w_i, \beta, \lambda) \\ &= \frac{p_{klc}\Pr(H_{i1},\ldots H_{iT} \mid S_i, x_i, H_{i0}, w_i, \rho_i = \rho_{lc}, \mu_i = \mu_c, \theta = \theta_{kc}, \beta, \lambda)}{\Pr(H_{i1},\ldots H_{iT} \mid S_i, x_i, H_{i0}, w_i, \beta, \lambda)} \end{aligned} \tag{B.2}$$

M-step: Substitute p_{klc} with p_{iklc} in (B.1.) 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 E and M steps are alternated until the relative difference in two successive set of parameters (Euclidean norm) is less than a tolerance criterion. Tolerance is set to 1e-3 for model selection and to 1e-6 for the final estimates. To speed up the estimation in the phase of model selection, we apply a trimming procedure in the M-step by setting p_{iklc} to 0 whenever p_{iklc} is lower than 1e-12. 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 on average with ten different sets of randomly chosen starting weights for each model specification in order to be sure that we had identified global maxima. For our final estimates, we have also tested ten different sets of starting weights, and eight cases resulted in the same global maximum. The robustness of the results were eventually checked with a simulated annealing procedure (Celeux et al., 1996).

Finally, the variance of the estimator is computed by Louis' formula (Louis, 1982), with computation of likelihood scores at the level of households to account for the panel dimension of the data.

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. As our main objective is to identify the individual heterogeneity in the relationship between life events, we have chosen to focus on the statistical fit of the model. Following the usual practice in applied literature, we here rely on a penalized-likelihood criterion – the Bayesian Information Criterion (BIC: McLachlan and Peel, 2000, chap. 6). The lower is the BIC the better is the fit. Alternative information criterion, such as the Akaike Information Criterion or the Consistent Akaike Information Criterion, do not change the choice of the final specification. Note also that it is difficult 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.

There are a large number of candidate specifications. We have chosen to restrict our attention to specifications with C=2 or C=3, a maximum of four components for the autoregressive parameter ρ, and the same number of components K_c for all c. We have been unable to estimate consistently models with K_c greater than 7. When the number of components $\sum_c K_c L_c$ becomes large, then the mass of one or several components tend to zero. Therefore, Table B1 below reports *BIC* values only for the specifications for which estimation was easily reproducible: convergence to the same global maximum for a number of different starting values.

In a pre-selection step, we set tolerance at 1e-3 and the trimming parameter at 1e-6. Increasing the number of points for the distribution of the intercept and the variance (K_c) increases the fit (lower BIC). The model with C=3 components for modeling the heterogeneity in the short-term impact of life events (μ), $L_c=1$ and $K_c=5$, seems to provide the best fit. However, increasing K_c to 6, does not result in a large loss of quality. Hence, in a second step (bottom line), we have tightened up the convergence criterion (to 1e-6) and relaxed the trimming parameter (to 1e-32). Note that the BIC decreases again and, now, the specification with C=3, L_c=1 and K_c=6 provides the best fit.

Table B1: BIC

C ↓	L_1 ↓	L_2 ↓	L_3 ↓	K_c →	4	5	6	7
				Step 1: convergence tolerance = 1^{e-3}; trimming = 1^{e-6}				
2	1	1		BIC	287124	286763	286581	**286527**
2	2	1		BIC	286788.97	286539	**286501**	
2	2	2		BIC	286647	286552	**286463**	
3	1	1	1	BIC	286540	**286452**	286480	
				Step 2: convergence tolerance = 1^{e-6}; trimming = 1^{e-32}				
3	1	1	1	BIC		286210	**286159**	

Figure 2 illustrates the fit of the model. The left panel 2a presents in grey the estimated density functions of psychological health for each of the 18 components. The black line represents the empirical density of psychological health for the estimation sample. The right panel 2b presents the same estimated density functions, scaled by their weights in the population. They add up to adjust to the empirical density of psychological health in black.

Appendix C: Derivation of Cognitive Ability and Personality Traits

Cognitive ability is measured in Wave 12 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 mean zero and standard deviation one.

Personality is measured in HILDA in Waves 5 and 9 using a version of the Big-5 Personality Inventory in which 5 personality traits are quantified: extraversion, agreeableness, conscientiousness, emotional stability (sometimes reversed and labelled neuroticism), and openness to experience. 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. Most individuals in our estimation sample are assigned personality values from Wave 5 (87%), but individuals with missing Wave 5 information are assigned personality values from Wave 9.

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 and 11 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 on the index 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 (Wave 3, for 75% of respondents).