Does Time Heal All Wounds? Life Satisfaction Trajectories in Australian Middle-Aged Women Before and After Relationship Dissolution

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Author Note

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Abstract

Divorce and separation are some of the most traumatic life events experienced by women and pose serious wellbeing consequences. Specifically, the impact of later-life relationship dissolution has been neglected in the literature. This study aimed to compare life satisfaction trajectories of Australian middle-aged women who did, and did not, experience relationship dissolution, and examine why some women adjust better than others. Prospective longitudinal data came from nine waves of the Australian Longitudinal Study on Women's Health. Women who divorced or separated during the study (*n* = 1,462) were propensity-score matched to women who remained married or partnered (*n* = 2,666). Results from Bayesian piecewise latent growth curve modelling indicate stable life satisfaction before relationship dissolution, a sudden decline in the years surrounding the event, and long-term curvilinear increases thereafter. Matched controls showed stability and slight increases in life satisfaction across the observation period, which suggests that at least some change in life satisfaction experienced by divorced and separated women is associated with relationship dissolution. Divorced and separated women showed larger individual differences in change, compared to matched controls, in the years before and surrounding dissolution. A moderate to large amount of variance in life satisfaction trajectories was explained by psychosocial and demographic moderators. Social support, perceived control, and subjective income were significant positive moderators of women's adjustment to relationship dissolution. Implications regarding wellbeing interventions for middle-aged women are discussed.

Keywords: life satisfaction, divorce, longitudinal, latent growth modelling

Declaration

This thesis contains no material which has been accepted for the award of any other degree or diploma in any University, and, to the best of my knowledge, this thesis contains no material previously published except where due reference is made. I give permission for the digital version of this thesis to be made available on the web, via the University of Adelaide's digital thesis repository, the Library Search and through web search engines, unless permission has been granted by the School to restrict access for a period of time.

Contributor Roles Table

ROLE	ROLE DESCRIPTION	STUDENT	SUPERVISOR 1	SUPERVISOR 2
CONCEPTUALIZATION	Ideas; formulation or evolution of overarching research goals and aims.	X		
METHODOLOGY	Development or design of methodology; creation of models.	X	X	
PROJECT ADMINISTRATION	Management and coordination responsibility for the research activity planning and execution.	X		
SUPERVISION	Oversight and leadership responsibility for the research activity planning and execution, including mentorship external to the core team.		X	
RESOURCES	Provision of study materials, laboratory samples, instrumentation, computing resources, or other analysis tools.		X	
SOFTWARE	Programming, software development; designing computer programs; implementation of the computer code and supporting algorithms; testing of existing code.			
INVESTIGATION	Conducting research - specifically performing experiments, or data/evidence collection.			
VALIDATION	Verification of the overall replication/reproducibility of results/experiments.	X	X	
DATA CURATION	Management activities to annotate (produce metadata), scrub data and maintain research data (including software code, where it is necessary for interpreting the data itself) for initial use and later re-use.	X	X	
FORMAL ANALYSIS	Application of statistical, mathematical, computational, or other formal techniques to analyze or synthesize study data.	X	X	
VISUALIZATION	Visualization/data presentation of the results.	X	X	
WRITING – ORIGINAL DRAFT	Specifically writing the initial draft.	X		
WRITING – REVIEW & EDITING	Critical review, commentary or revision of original draft	X	X	

Does Time Heal All Wounds? Life Satisfaction Trajectories in Australian Middle-Aged Women Before and After Relationship Dissolution

Whether life satisfaction fully recovers after a divorce or separation is a subject of debate. Questions also remain as to how long any recovery takes, and why some people adjust better than others. This is especially pertinent to the Australian context, as Australia was one of the first countries to introduce no-fault divorce and recognise de facto relationships as equal to marriage in critical respects (Family Law Act, 1975).

Divorce and separation rates have increased more for middle to older aged adults, compared to any other age group (Brown & Lin, 2012). According to the Pew Research Center, the divorce rate for US adults aged 50 years and older doubled between 1990 and 2015 (Stepler, 2017). A similar trend has been observed in Australia (Qu & Baxter, 2023). Yet, compared to their younger counterparts, older adults have been largely neglected in literature on adjustment to relationship dissolution (Brown & Lin, 2012). Given that Australia has an ageing population (Australian Institute of Health and Welfare, 2023), interventions specifically tailored for this age group are necessary to improve life satisfaction.

Life satisfaction is one’s cognitive judgement about their quality of life overall and in central life domains (e.g., work, relationships, and health; Diener, 1984; Sirgy, 2021). Life satisfaction is related to, but differs from, other indicators of subjective wellbeing, such as happiness or low distress (Diener et al., 2013). Whereas measures of happiness and distress are designed to capture affect, life satisfaction is thought to represent lifetime goal attainment (Sirgy, 2021). High life satisfaction levels have been found to correlate with better health, higher productivity, and lower mortality risk (Diener & Chan, 2011; Diener et al., 2018; Lyubomirsky et al., 2005). Some researchers, therefore, suggest that life satisfaction is a useful indicator to inform health and wellbeing policy (Diener et al., 2018, Yap et al., 2014).

Researchers have observed that subjective wellbeing remains relatively stable over time, with only temporary fluctuations, regardless of one's experiences. This pattern has come to be known as 'hedonic adaptation' (see Luhmann & Intelisano, 2018 for a review). However, these early studies were limited by their cross-sectional nature. According to meta-analyses of longitudinal studies, life events can have profound long-term effects on subjective wellbeing, particularly life satisfaction (Bühler et al., 2023; Luhmann et al., 2012). These impactful events include the dissolution of both marital and de facto relationships (Amato, 2000; Sbarra & Whisman, 2022). A meta-analysis of 600 million people in 24 countries found that divorced and separated adults have a 30% higher risk of mortality than their married counterparts (Shor et al., 2012).

Impact of Relationship Dissolution on Women

Divorce continues to have more severe economic consequences for women than for men (Arber, 2004; Leopold, 2018; Raley & Sweeney, 2020). Moreover, the economic impact of separation from a cohabitating union has increased to equal that of divorce for women (Tach & Eads, 2015).

In line with global trends, the effects of divorce on life satisfaction and health in Australia have been shown to be more pervasive for women than for men (Gray et al., 2010). Moreover, these effects have been observed irrespective of whether the union was marital or non-marital (Amato, 2010; Wu & Hart, 2002). Given that recent research has found very similar life satisfaction trajectories across both divorce and separation (Asselmann & Specht, 2023), and that married and cohabitating individuals are treated equally in Australia (Family Law Act, 1975), it would be remiss to exclude women in de facto relationships from analyses of life satisfaction trajectories in Australia.

Life Satisfaction Trajectories Around Relationship Dissolution

Longitudinal research has indicated that divorcees show declines in their life satisfaction trajectories (Doré & Bolger, 2018; Lucas, 2005). There appear to be three distinct phases of the divorce process (Asselmann & Specht, 2023; van Scheppingen & Leopold, 2020). Firstly, life satisfaction levels decline in the years before divorce (Denissen et al., 2019; Lucas, 2005; Luhmann et al., 2012). This 'anticipation effect' may be due to increased marital problems (Amato & Hohmann-Marriott, 2007). Secondly, there appears to be a marked decline in life satisfaction in the year surrounding divorce (Asselmann & Specht, 2023; van Scheppingen & Leopold, 2020). Thirdly, life satisfaction increases to some degree after divorce (Bühler et al., 2023; Luhmann et al., 2012).

Questions remain regarding the extent to which one's life satisfaction can recover to pre-divorce levels. Some longitudinal studies found that individuals regain their pre-divorce life satisfaction levels within 5 years (Asselmann & Specht, 2023; Clark & Georgellis, 2013). Others have shown incomplete recovery in the same period (Denissen et al., 2019; Lucas, 2005). However, due to anticipatory declines in life satisfaction before divorce, it is unclear whether life satisfaction levels in the preceding five years reflect one's true baseline (Luhmann et al., 2012). As such, longer-term prospective longitudinal studies are required.

Another major limitation of existing longitudinal research is its inability to disentangle divorce-induced change in life satisfaction from other normative changes (Luhmann & Intelisano, 2018). One way to address this issue is to include a control group of married individuals, then conduct propensity-score matching to account for pre-existing differences in life satisfaction and demographic variables (e.g., Anusic et al., 2014; van Scheppingen & Leopold, 2020). Using this technique, van Scheppingen and Leopold (2020) found that divorced individuals did not regain their pre-divorce life satisfaction levels, and that married controls exhibited continuous gradual declines throughout the study. This finding indicates that not all changes in life satisfaction can be attributed to divorce. Therefore, any investigation of life satisfaction trajectories around relationship events in other national samples would benefit from employing propensity-score matching.

Individual Differences in Life Satisfaction Trajectories

In addition to examining the association between relationship dissolution and mean-level change in life satisfaction, many reviews have emphasised the need to investigate individual differences in life satisfaction trajectories (Amato, 2010; Luhmann et al., 2012; Luhmann & Intelisano, 2018; Lin & Brown, 2020). The predominant theoretical framework in the field, the ‘divorce-stress-adjustment perspective,’ explains individual differences in wellbeing trajectories through two contrasting models (Amato, 2000). First, the ‘crisis model’ characterises divorce as a disruption to which people fully adjust, and in which the rate of adjustment is determined by personal resources (e.g., coping skills or social support). Second, the ‘chronic strain model’ posits that divorce involves enduring stressors (e.g., economic hardship and sole parenting), which can indefinitely impact wellbeing. Although this model assumes that divorcees do not regain their pre-divorce wellbeing levels, the amount of distress experienced is influenced by their personal resources. However, the exact nature of stressors and resources which may moderate life satisfaction trajectories remains unclear.

One potential moderator of adjustment to divorce may be marital distress, reflected by reduced life satisfaction before the event. Van Scheppingen and Leopold (2020) found that change in life satisfaction post-divorce was negatively predicted by life satisfaction levels in the preceding phases. Specifically, individuals who had lower baseline life satisfaction, or who experienced sharper declines in the year of divorce, reported larger increases post-divorce. These authors also examined the role of time-invariant moderators, such as having children, but found no significant effects on life satisfaction trajectories. This finding contrasts with previous longitudinal research, which has shown that people with children experience greater declines in life satisfaction post-divorce (Leopold & Kalmijn, 2016; Williams & Dunne-Bryant, 2006). Given these mixed results from U.S. and German data, it would be of interest to investigate the moderating effect of having children in an Australian sample.

Very few studies have examined time-varying moderators of life satisfaction trajectories around divorce. For example, longitudinal research has found psychosocial factors, such as social support (Yu & Liu, 2021) and perceived control (Infurna et al., 2016), to be protective against wellbeing declines following other life events. Given that previous literature examining only time-invariant moderators (e.g., van Scheppingen & Leopold, 2020) has been unable to account for much of the variance in post-divorce wellbeing outcomes (Lin & Brown, 2020), further research incorporating a broader range of explanatory factors is required.

In addition, there remains limited longitudinal evidence for socioeconomic status (SES) as a moderator of the association between divorce and wellbeing (Sbarra & Whisman, 2022). Lower education levels have been shown to predict a declining life satisfaction trajectory after divorce (Mancini et al., 2011), but the role of income remains less clear. More prospective designs using propensity-matched control groups are needed to investigate the role of socioeconomic factors and whether any effects are exclusive to those who experience relationship dissolution.

Furthermore, re-partnering after relationship dissolution has been associated with increased life satisfaction (Gloor et al., 2021; Lucas, 2005). Given the lack of research on re-partnering and life satisfaction in older adults (Brown et al., 2019), it is worth replicating this finding with a prospective study design and larger sample.

Notably, many studies assume that individual differences in life satisfaction trajectories are due to relationship dissolution, as opposed to other normative processes. Yet, this is impossible to determine without a control group. Van Scheppingen and Leopold (2020) found that, in the post-divorce phase, there was more variability of life satisfaction outcomes among the divorced group than the married controls, implying that individual differences were associated with divorce. Future research on individual differences in adjustment to life events should therefore include a propensity-matched control group.

Present Study

To assist the design of much-needed wellbeing interventions following later-life divorce and separation, the present study aimed to investigate mean-level life satisfaction trajectories for middle-aged Australian women before and after relationship dissolution. Our second aim was to disentangle the effects of relationship dissolution from other normative changes by employing a propensity-matched control group. The final aim was to examine sources of individual differences in life satisfaction trajectories surrounding relationship dissolution. We drew upon data from nine waves of the Australian Longitudinal Study on Women's Health (ALSWH), a large population-based survey measuring numerous health and wellbeing factors in over 57,000 women, across four birth cohorts (Lee et al., 2005). The study allows for a prospective design using piecewise growth modelling, a special case of structural equation modelling (SEM; Duncan et al., 2013). This technique provides a flexible framework to model phasic change that occurs at different times across individuals. It also enables examination of predictors of individual differences in growth for each phase (Hesser, 2015). There are several psychosocial and demographic variables available in the ALSWH, which we incorporated as moderators, i.e., social support, perceived control, having children, subjective income, and education.

It was hypothesised that:

1a. Participants who experience relationship dissolution will exhibit declines in life satisfaction before the event, followed by a sudden decline in the years surrounding the event, and increases in the years after.

1b. Participants who remain married or partnered will experience small, but continuous, declines in life satisfaction across the study period.

2. Participants who experience relationship dissolution will show larger individual differences in life satisfaction change than those who remain married or partnered throughout the study period.

3. Change in life satisfaction before relationship dissolution will be negatively associated with change after relationship dissolution.

4. Certain demographic and psychosocial factors will act as moderators of individuals' life satisfaction trajectories; namely, having children, education, subjective income, social support, perceived control, and re-partnering.

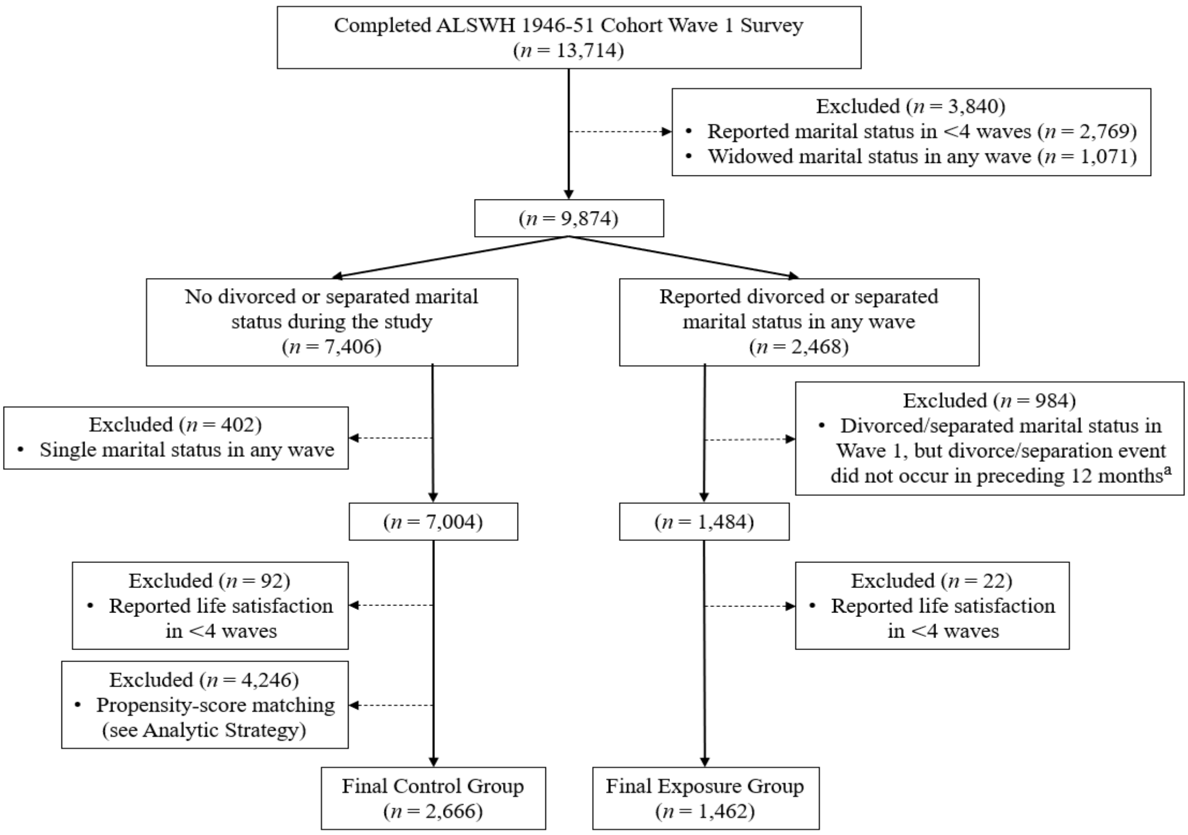
Method

Participants

Participants were women from the 1946-51 birth cohort of the ALSWH, all of whom were Australian citizens or permanent residents. The analysis used data from survey waves one to nine, collected between 1996 and 2019 at 3-yearly intervals, except for Wave 2 (1998; 2 years after Wave 1). Participants were aged 45 to 50 in Wave 1 and 68 to 73 in Wave 9. Selection of women who divorced or separated during the study (exposure group; n = 1,462) and remained married or partnered throughout (control group; n = 2,666) is outlined in Figure 1. We find our sample size to be adequate as Muthén and Curran (1997) recommended at least 500 participants per group for latent growth modelling.

Figure 1

Participant Selection Flowchart



Note. Our minimum threshold of 4 non-missing waves aligns with previous literature on latent growth modelling (Duncan & Duncan, 2009; Sivo & Willson, 1998).

[a]Life event checklist (Australian Longitudinal Study on Women's Health [ALSWH], 2020a; Brilleman, n.d.)

Procedure

The sampling procedure used in the ALSWH has been widely documented (Dobson et al., 2015; Lee et al., 2005). For the 1946-51 birth cohort, women were selected from the Medicare database and sent invitations by mail. Sampling was random, however women from regional areas were sampled at double the rate of women from urban areas to ensure adequate representation in statistical comparisons. After informed consent was obtained, participants were surveyed approximately every three years via mail. No further participants were recruited for this cohort after the commencement of the study. Of the 13,714 women who completed the Wave 1 survey (1996), 7,956 participated in Wave 9 (2019). The most common reason for non-response was the inability to contact eligible women (ALSWH, 2020b).

In Wave 1, the ALSWH sample was largely representative of the Australian population, compared to the 1996 census, although ALSWH respondents with tertiary qualifications were over-represented and non-Australian born women were under-represented (Brown et al., 1999). These discrepancies have grown in subsequent waves. In Wave 3, ALSWH respondents were also more likely to be married and have more highly paid occupations, and Indigenous women were under-represented (Powers, 2004). Previous literature identified low education, non-English speaking background, smoking behaviour, low income, and poor health as correlates of attrition between Waves 1 and 2 (Young et al., 2006).

Permission to use the data was obtained from the ALSWH via the Australian Data Archive (Australian Government Department of Health, 2022). The ALSWH was approved by the Human Research Ethics Committees at the University of Queensland (EC00144) and University of Newcastle (EC00456/7; ALSWH, 2020c).

Measures

Life Satisfaction (Outcome Variable)

Life satisfaction was assessed in all nine waves using a custom ALSWH measure with seven items (Fitzgerald, n.d.). The measure asked, “in general, are you satisfied with what you have achieved in your life so far in the areas of: work, career, study, family relationships, partner/closest personal relationship, friendships and social activities.” Ratings for each domain were provided on a 4-point Likert scale, ranging from 1 (*very satisfied*) to 4 (*very dissatisfied*). Scores were reversed and then averaged to form the total life satisfaction score, whereby higher scores represent higher life satisfaction. The measure only contained five items in the first wave, as the work, career, and study domains were combined. This measure has acceptable internal reliability ($\alpha = .79$) in the ALSWH 1946-51 cohort (Lee & Gratmotnev, 2007) and several studies have demonstrated its appropriate psychometric properties in both young and middle-aged women (Beatty et al., 2012; Eime et al., 2010; Johnstone & Lucke, 2022).

Marital Status (Selection Variable)

Marital status, with the options, “married,” “de facto,” “divorced,” “separated,” “widowed,” and “single/never married,” was assessed in all nine waves. When selecting participants, we collapsed the “married” and “de facto” categories, and the “divorced” and “separated” categories. Relationship dissolution was therefore defined as a change in marital status from married/de facto in one wave to divorced/separated in the next wave.

Perceived Control (Moderator)

Perceived control was assessed in Waves 3 to 9, using the 6-item Life Control Scale (Bobak et al., 1998). The two positively worded items, e.g., “*at home, I feel I have control over what happens in most situations,*” are scored from 0 (*strongly disagree*) to 5 (*strongly agree*). Scoring is reversed for the four negatively skewed items (e.g., “*I often have the* *feeling that I am being treated unfairly"*). Scores from each item are summed to form a total score out of 30, whereby higher scores represent higher perceived control. This scale has acceptable internal consistency (α = .71) in the ALSWH 1946-51 birth cohort (Lee et al., 2009). Perceived control values were divided by 6 for SEM analyses to ensure model convergence.

Social Support (Moderator)

Social support was assessed in Waves 2 to 9, using a 6-item version of the Medical Outcomes Study Social Support Survey (MOS-SSS), which was developed for the ALSWH (Russell & Smith, 2002; Sherbourne & Stewart, 1991). Respondents rated their perception of support received in six areas (e.g., sharing their worries, and being taken to the doctor). Items are measured on a five-point Likert scale, ranging from 1 (none of the time) to 5 (all of the time). The total score is the mean of items. The scale has high internal consistency (α = .90) in the ALSWH 1946-51 birth cohort, and a single-factor structure (Holden et al., 2014).

Re-Partnering (Moderator)

Re-partnering was a binary variable (1 = yes, 0 = no), created to measure whether participants' marital status changed from divorced or separated to married or de facto at any point after relationship dissolution.

Children (Moderator)

Having children was a binary variable (1 = yes, 0 = no), created from an item measuring satisfaction with childcare arrangements in Wave 1 (ALSWH, 2020a). Since respondents were instructed to skip the item if they did not have children, the ALSWH research team ascribed a "no children" response code to these individuals.

Subjective Income (Moderator)

Subjective income was assessed in all nine waves using a single item, "*how do you manage on the income you have available?"* (Egan et al., 2020). Scores were on a 5-point scale, ranging from 1 (*it is impossible*) to 5 (*it is easy*). The categories (1) "it is impossible" and (2) "it is difficult" were collapsed due to few participants (162 total) falling into Category 1. For SEM analyses, we used the average of Likert scale responses.

Education (Moderator)

Education was assessed in Waves 1, 2 and 6 as participants' highest qualification attained (ALSWH, 2020a). For propensity-score matching, we collapsed the seven response options ("no formal qualifications," "school or intermediate certificate," "higher school or leaving certificate," "trade/apprenticeship," "certificate/diploma," "university degree," or "higher university degree") into three categories: *school only*, *vocational training* and *university degree*. For SEM analyses, we further collapsed the *vocational training* and *university degree* categories to create a binary variable, ensuring model convergence.

Matching Variables

Variables used for propensity matching, but not used as moderators in the main analysis, are described in Appendix A.

Analytic Strategy

Propensity-Score Matching

To control for pre-existing group differences, we conducted propensity-score matching (Rosenbaum & Rubin, 1983), using the psmatch2 package (Leuven & Sianesi, 2003) in Stata Version 17 (StataCorp, 2021). We matched the exposure group to the control group on several health and demographic variables measured in Wave 1. A propensity score was estimated for each participant, representing the likelihood that they will experience relationship dissolution, given the values of the covariates. For participants with missing data on one or more covariates, we imputed the missing values on covariates using the *mice* package (van Buuren & Groothuis-Oudshoorn, 2011) in R Version 4.2.3 (R Core Team, 2023). The imputation was run using all matching variables as predictors of missingness with

20 datasets but selecting just the first for propensity-score matching. We employed one-to-many matching with replacement, and a nearest neighbour algorithm to find the three best matches for exposure group participants based on propensity scores (e.g., van Scheppingen & Leopold, 2020). Our maximum acceptable propensity-score difference between matches was a caliper width of .2 *SD*s of the logit of the propensity score (Austin, 2011; van Scheppingen & Leopold, 2020). The exposure group (*n* = 1,462) was matched to 2,666 control respondents in total. All imputed values were set back to missing for further modelling.

Unconditional Piecewise Growth Curve Modelling

To test Hypotheses 1a and 1b, we used Bayesian piecewise latent growth curve modelling (e.g., Stronge et al., 2021; van Scheppingen & Leopold, 2020) in Mplus Version 8.8 (Muthén & Muthén, 2017). Full Information Maximum Likelihood (FIML) estimation was used to address missing data. Adequate model fit was indicated by the comparative fit index (CFI) $>$ .90, Tucker-Lewis Index (TLI) $>$ .90, and root mean square error of approximation (RMSEA) $<$ .08 (Hu & Bentler, 1998).

First, we created an artificial measurement wave of relationship dissolution for each control participant by imputing the dissolution wave of their exposure group match. This provided a comparable time scale to investigate between-group differences in life satisfaction trajectories.

To examine mean-level change in life satisfaction, we constructed 22 piecewise models, centred around the measurement wave in which relationship dissolution occurred. We selected the models to encompass every combination of no change, linear change, and quadratic change, across one, two, or three phases (e.g., van Scheppingen & Leopold, 2020). The best-fitting model was determined by the lowest Bayesian Information Criterion (BIC) value (Schwarz, 1978). If the difference in BIC values between the most promising models was less than two, we selected the more parsimonious model – that is, one hypothesising linear rather than quadratic change (e.g., van Scheppingen & Leopold, 2020). Model specifications are presented in Appendix B.

If a one-phase model (1a-c) had the best fit, this would suggest no effect of relationship dissolution. The two-phase models (2a-h) represented change in life satisfaction both before and after dissolution. The three-phase models (3a-k) also captured sudden change immediately surrounding dissolution.

Subsequently, we used a multiple-group Bayesian piecewise latent growth curve model to test whether the exposure group and control group differed in (a) mean-level change in life satisfaction, and (b) heterogeneity in change (Hypothesis 2). The script is provided in Appendix C.

Conditional Piecewise Growth Modelling

To examine individual differences in life satisfaction trajectories, we first tested whether change in life satisfaction during one phase of relationship dissolution was correlated with change in preceding phases (Hypothesis 3). Specifically, we added latent parameters (e.g., intercept, slopes) of life satisfaction in a preceding phase as predictors of latent parameters in a following phase (e.g., van Scheppingen & Leopold, 2020). As a second step, we addressed Hypothesis 4 by adding moderators of life satisfaction trajectories (i.e., re-partnering, children, perceived control, social support, subjective income, education). For time-varying moderators (i.e., social support, perceived control, and subjective income), we averaged the values for each individual across waves that corresponded to each phase of relationship dissolution (see Results).

Results

Participants

For the models outlined in the Method, we included observations from eight measurement waves (i.e., 24 years) before and after the wave in which relationship dissolution occurred. The sample size in the exposure group and control group across each measurement point is displayed in Table 1.

Table 1

Number of Life Satisfaction Responses per Measurement in the Exposure and Control Groups

		Exposure group		Control group	
		n	%	*n*	%
Total		1,462	100.0	2,666	100.0
Year	−22.5	40	2.7	83	3.1
	−19.5	108	7.4	199	7.5
	−16.5	163	11.1	301	11.3
	−13.5	256	17.5	495	18.6
	−10.5	370	25.3	741	27.8
	−7.5	531	36.3	1076	40.4
	−4.5	998	68.3	1975	74.1
	−1.5	1,144	78.2	2285	85.7
	1.5	1,442	98.6	2416	90.6
	4.5	1,264	86.5	2314	86.8
	7.5	1,187	81.2	2163	81.1
	10.5	1,063	72.7	1987	74.5
	13.5	933	63.8	1699	63.7
	16.5	793	54.2	1407	52.8
	19.5	610	41.7	1063	39.9
	22.5	261	17.9	387	14.5
	25.5	99	6.8	111	4.2

Note. Years are centred around relationship dissolution. The 1.5-year increments represent uncertainty about the exact time at which relationship dissolution occurred between the 3-yearly measurement waves.

Sample descriptive statistics at Wave 1 are displayed in Table 2. After propensity-score matching, standardised mean differences between the exposure and control groups were below the threshold for small effect sizes (i.e., Cohen's $d < .2$ and Cramer's $V < .1$; Cohen, 1988; Kim, 2017) on all matching variables, except home ownership. Descriptive statistics for moderator variables not shown in Table 2, or which were altered for the conditional models, are available in Appendix D.

Table 2

Descriptive Statistics (Wave 1) and Standardised Group Differences Before and After Propensity-Score Matching

Matching variable	Exposure group (n = 1,462) M (SD)	Unmatched controls (n = 6,912) M (SD)	Cohen's d	Matched controls (n = 2,666) M (SD)	Cohen's d
Life satisfaction	3.00 (0.52)	3.25 (0.47)	d = .49***	3.09 (0.49)	d = .18***
Mental health (SF-36)	46.79 (11.68)	50.24 (9.88)	d = .32***	48.19 (10.76)	d = .13***
Physical health (SF-36)	50.45 (8.96)	50.46 (8.42)	d = .00	50.48 (8.46)	d = .00
Matching variable	n (%)	n (%)	Cramer's V	n (%)	Cramer's V
Age (years)			V = .04*		V = .02
45	305 (20.9)	1,212 (17.5)		534 (20.0)	
46	322 (22.0)	1,465 (21.2)		579 (21.7)	
47	274 (18.7)	1,371 (19.8)		500 (18.8)	
48	250 (17.1)	1,275 (18.4)		472 (17.7)	
49	278 (19.0)	1,394 (20.2)		511 (19.2)	
50	33 (2.3)	195 (2.8)		70 (2.6)	
Language spoken at home			V = .01		V = .01
English	1,380 (95.9)	6,505 (95.6)		2,494 (95.3)	
Other	59 (4.1)	300 (4.4)		122 (4.7)	
Location			V = .03*		V = .02
Urban	547 (37.4)	2,374 (34.4)		959 (36.0)	
Regional	560 (38.3)	2,691 (38.9)		1,030 (38.6)	
Remote	355 (24.3)	1,846 (26.7)		677 (25.4)	
Employment			V = .05***		V = .03
Not working	409 (28.5)	2,188 (32.1)		765 (29.3)	
1 – 24 hours/week	306 (21.3)	1,589 (23.3)		552 (21.1)	
25 – 34 hours/week	175 (12.2)	843 (12.4)		361 (13.8)	
35 – 48 hours/week	446 (31.1)	1,865 (27.4)		786 (30.1)	
49+ hours/week	99 (6.9)	321 (4.7)		150 (5.7)	
Housing situation			V = .10***		V = .07***
House	1,228 (89.6)	6,223 (95.4)		2,335 (93.4)	
Flat/unit/apartment	76 (5.5)	168 (2.6)		82 (3.3)	
Caravan/tent/other	67 (4.9)	131 (2.0)		83 (3.3)	
Home ownership			V = .26***		V = .17***
Self	281 (20.6)	265 (4.1)		223 (9.0)	
Partner	274 (20.1)	1,317 (20.3)		531 (21.4)	
Partner and self	713 (52.3)	4,643 (71.5)		1,587 (63.9)	
Others	95 (7.0)	271 (4.2)		143 (5.8)	
Children [a]			V = .01		V = .01
Yes	937 (66.3)	4,581 (67.7)		1,718 (65.6)	
No	477 (33.7)	2,186 (32.3)		899 (34.4)	
Education [a]			V = .03**		V = .02
School only	940 (64.8)	4,519 (65.9)		1,705 (64.6)	
Vocational training	271 (18.7)	1,405 (20.5)		527 (20.0)	
University degree	239 (16.5)	933 (13.6)		406 (15.4)	
Subjective income [a]			V = .12***		V = .07***
It is easy	197 (13.5)	1,256 (18.2)		402 (15.2)	
Not too bad	546 (37.4)	3,160 (45.9)		1,108 (41.8)	
Difficult sometimes	441 (30.2)	1,788 (26.0)		773 (29.2)	
Difficult always	231 (15.8)	560 (8.1)		309 (11.7)	
Impossible	43 (2.9)	119 (1.7)		56 (2.1)	

Note. Percentages do not include missing data.

[a] Denotes matching variables which were also used as moderators in the conditional piecewise growth models.

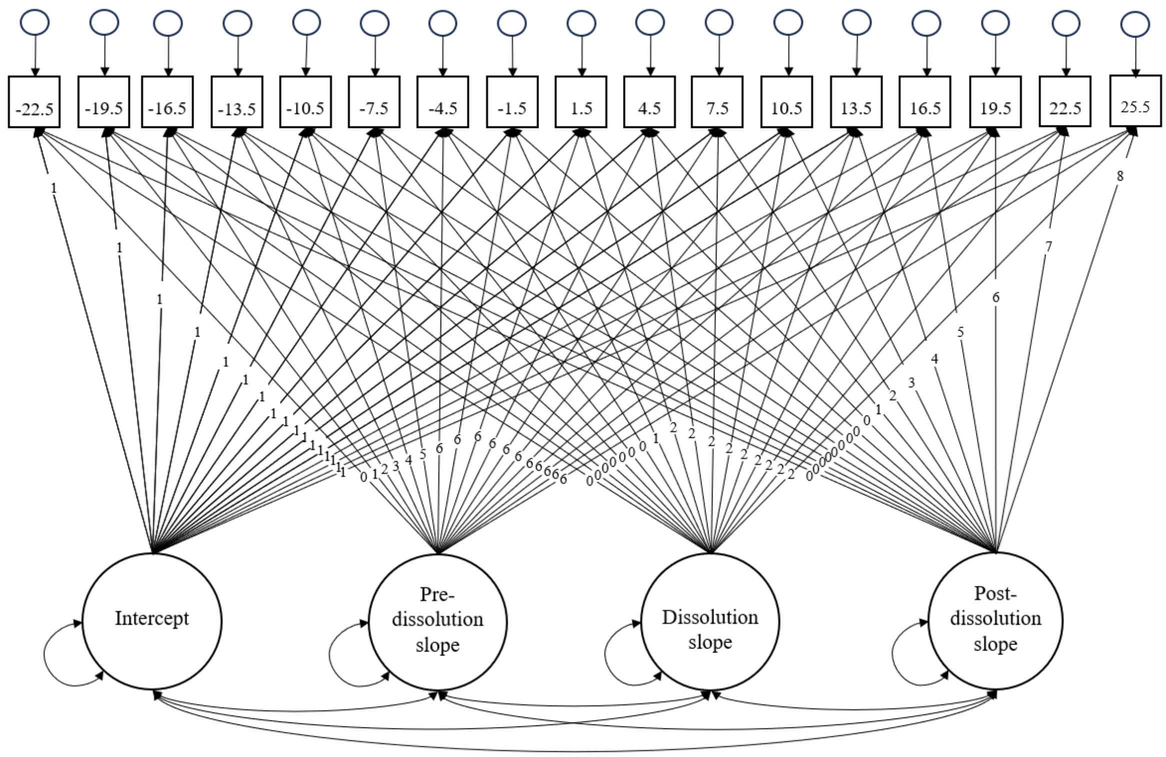
*.01 < $p \leq .05$ **.001 < $p \leq .01$ ***$p \leq .001$

Hypotheses 1a and 1b: Mean-Level Change in Life Satisfaction

Hypotheses 1a and 1b predict three phases of change in life satisfaction for the exposure group (i.e., gradual declines before, a sudden decline during, then gradual increases after dissolution) and continuous declines for the control group. To determine mean-level life satisfaction trajectories, we constructed 22 Bayesian piecewise latent growth curve models for each group (e.g., van Scheppingen & Leopold, 2020). Mplus specifications for the models are available in Appendix B and the set-up of a three-phase linear model is shown in Figure 2.

Figure 2

Unconditional Piecewise Growth Curve Model for Life Satisfaction (Model 3h)



Note. Observed life satisfaction variables (squares) are measured from 22.5 years before relationship dissolution to 25.5 years after dissolution. The four latent variables (circles) represent baseline life satisfaction 22.5 years before dissolution (*intercept*, all factor loadings set to 1), long-term linear change before dissolution (*pre-dissolution slope*, factor loadings 0,1,2,3,4,5,6,6,6,6,6,6,6,6,6,6,6), linear change in the 3 years surrounding dissolution (*dissolution slope*, factor loadings 0,0,0,0,0,0,0,1,2,2,2,2,2,2,2,2,2), and long-term linear change after dissolution (*post-dissolution slope*, loadings 0,0,0,0,0,0,0,0,0,1,2,3,4,5,6,7,8). The variances of the intercept and slopes were freed and allowed to covary (e.g., van Scheppingen & Leopold, 2020).

Model fit indices are displayed in Tables 3 and 4 for the exposure and control groups, respectively. The best-fitting model for life satisfaction in both groups was Model 3i, based on BIC values. The model specifies linear trends for the pre-dissolution and dissolution phases, and a quadratic trend for the post-dissolution phase.

Table 3

Fit indices for 22 Models of Life Satisfaction in the Exposure Group

Model	Slope Components	BIC	CFI	TLI	RMSEA
	One-phase models – *no effect of relationship dissolution*				
1a	Intercept only	11,444.199	0.839	0.855	0.069
1b	Linear	10,783.007	0.943	0.948	0.041
1c	Quadratic	10,582.753	0.975	0.976	0.028
	Two-phase models – *gradual effect of dissolution*				
2a	Gradual linear + no change	11,051.629	0.898	0.907	0.055
2b	Gradual linear + gradual linear	10,595.968	0.972	0.973	0.030
2c	Gradual linear + gradual quadratic	10,537.234	0.986	0.986	0.021
2d	No change + gradual linear	10,747.858	0.946	0.951	0.040
2e	No change + gradual quadratic	10,584.609	0.975	0.976	0.028
2f	Gradual quadratic + gradual quadratic	10,504.089	0.997	0.997	0.010
2g	Gradual quadratic + gradual linear	10,570.368	0.981	0.982	0.024
2h	Gradual quadratic + no change	11,045.329	0.903	0.910	0.055
	Three-phase models – sudden effect of dissolution				
3a	No change + sudden change + no change	11,177.312	0.881	0.890	0.060
3b	Gradual linear 1 + sudden + gradual linear 1	10,465.455	0.972	0.973	0.030
3c	Gradual quadratic 1 + sudden + gradual quadratic 1	*Model 3c did not converge*			
3d	No change + sudden + gradual linear	10,413.689	0.999	0.999	0.006
3e	No change + sudden + gradual quadratic	10,401.512	1.000	1.000	0.000
3f	Gradual linear + sudden + no change	10,945.271	0.918	0.923	0.051
3g	Gradual quadratic + sudden + no change	10,970.959	0.919	0.922	0.051
3h	Gradual linear 1 + sudden + gradual linear 2	10,403.075	1.000	1.000	0.000
3i	**Gradual linear + sudden + gradual quadratic**	**10,397.082**	**1.000**	**1.000**	**0.000**
3j	Gradual quadratic + sudden + gradual linear	10,436.889	1.000	1.000	0.000
3k	Gradual quadratic 1 + sudden + gradual quadratic 2	10,440.573	1.000	1.000	0.000

Note. The best-fitting model based on fit indices is shown in bold. Selection of slope components was based on van Scheppingen and Leopold (2020).

Table 4

Fit indices for 22 Models of Life Satisfaction in the Control Group

Model	Slope Components	BIC	CFI	TLI	RMSEA
	One-phase models – *no effect of relationship dissolution*				
1a	Intercept only	17,556.989	0.895	0.905	0.057
1b	Linear	16,401.145	0.987	0.988	0.020
1c	Quadratic	16,319.543	0.994	0.994	0.014
	Two-phase models – *gradual effect of dissolution*				
2a	Gradual linear + no change	16,928.109	0.943	0.948	0.042
2b	Gradual linear + gradual linear	16,294.409	0.995	0.996	0.012
2c	Gradual linear + gradual quadratic	16,292.564	0.998	0.998	0.007
2d	No change + gradual linear	16,380.791	0.987	0.988	0.020
2e	No change + gradual quadratic	16,362.289	0.991	0.992	0.017
2f	Gradual quadratic + gradual quadratic	16,327.156	0.999	0.999	0.004
2g	Gradual quadratic + gradual linear	16,318.709	0.997	0.997	0.011
2h	Gradual quadratic + no change	16,912.501	0.946	0.949	0.042
	Three-phase models – *sudden effect of dissolution*				
3a	No change + sudden change + no change	17,157.180	0.926	0.932	0.048
3b	Gradual linear 1 + sudden + gradual linear 1	16,315.729	0.982	0.982	0.023
3c	Gradual quadratic 1 + sudden + gradual quadratic 1	*Model 3c did not converge*			
3d	No change + sudden + gradual linear	16,322.860	0.994	0.994	0.014
3e	No change + sudden + gradual quadratic	16,306.002	0.998	0.998	0.008
3f	Gradual linear + sudden + no change	16,807.676	0.955	0.957	0.038
3g	Gradual quadratic + sudden + no change	16,842.069	0.955	0.956	0.039
3h	Gradual linear 1 + sudden + gradual linear 2	16,291.650	0.998	0.998	0.007
3i	**Gradual linear + sudden + gradual quadratic**	**16,284.684**	**1.000**	**1.000**	**0.000**
3j	Gradual quadratic + sudden + gradual linear	16,331.113	0.999	0.999	0.007
3k	Gradual quadratic 1 + sudden + gradual quadratic 2	16,332.463	1.000	1.000	0.000

Note. The best-fitting model based on fit indices is shown in bold. Selection of slope components was based on van Scheppingen and Leopold (2020).

In partial support of Hypothesis 1a, the appropriateness of Model 3i indicates that change in life satisfaction around relationship dissolution is characterised by three phases. Specifically, as the model parameter values in Table 5 and Figure 3 show, the exposure group experienced stable life satisfaction before relationship dissolution, a sudden decline in the years around the event, and long-term curvilinear increases thereafter. The control group showed stable life satisfaction and slight curvilinear increases across the observation period, which did not support Hypothesis 1b.

Table 5

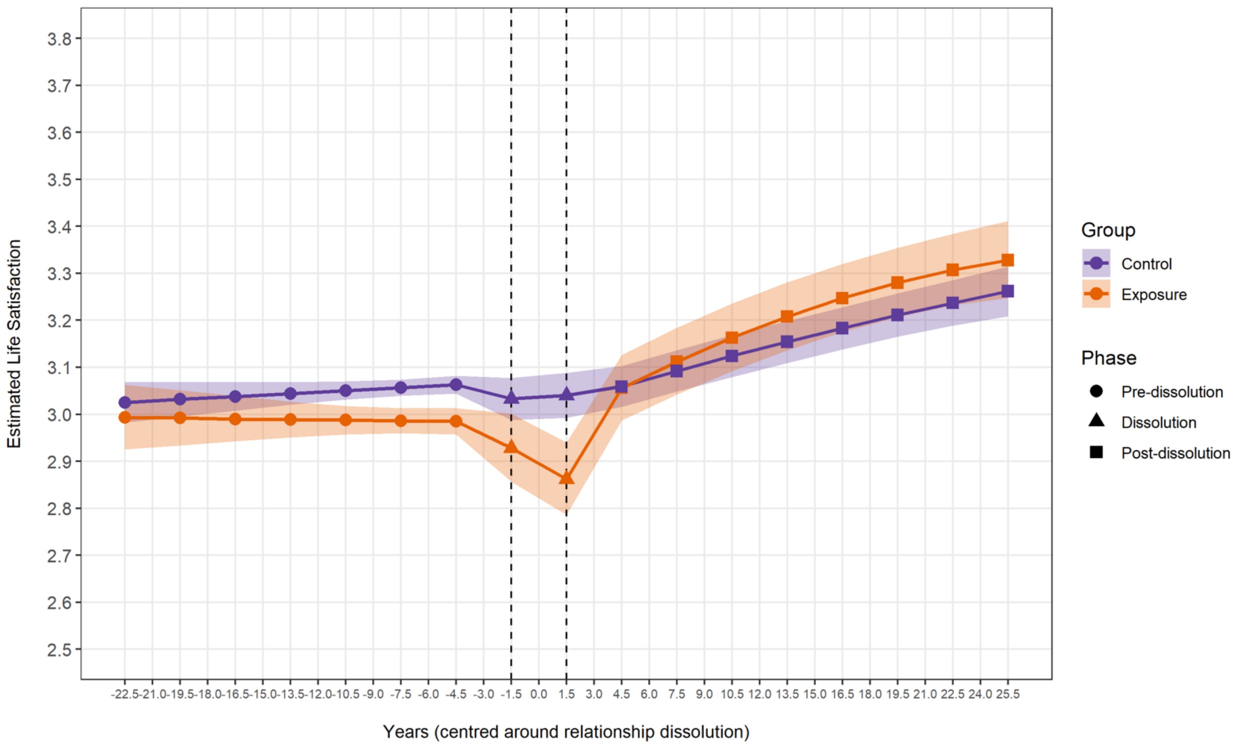
Mean Parameter Estimates of the Best-Fitting Model for Life Satisfaction in the Exposure Group and Control Group (Model 3i)

	Exposure Group				Control Group				Difference	
Parameter	Mean	*SE*	*p*	95% CI	Mean	*SE*	*p*	95% CI	Wald	*p*
Intercept	2.993	0.035	<.001	[2.925, 3.063]	3.025	0.002	<.001	[2.982, 3.068]	0.56	.453
Linear Δ1	−0.001	0.006	.414	[−0.014, 0.011]	0.006	0.004	.052	[−0.001, 0.014]	1.11	.291
Linear Δ2	−0.065	0.007	<.001	[−0.079, −0.052]	0.007	0.004	.041	[−0.001, 0.016]	80.99	<.001
Linear Δ3	0.066	0.006	<.001	[0.054, 0.077]	0.035	0.004	<.001	[0.027, 0.043]	17.26	<.001
Quadratic Δ3	−0.003	0.001	.001	[−0.005, −0.001]	−0.001	0.001	.148	[−0.002, 0.001]	4.04	.044

Note. CI = Credibility interval.

Figure 3

Estimated Life Satisfaction Trajectories for the Exposure and Control Groups



Note. The relationship dissolution event occurred between the two points depicted by dashed lines. The shaded ribbons represent 95% credibility intervals around mean estimates. The time scale for controls was based on the wave of dissolution of their exposure group matches. Intercepts and pre-dissolution slopes did not differ significantly between groups (see Table 5), rather, the gap between slopes reflects the fine-grained y-axis scale.

Mean-level life satisfaction in the exposure group recovered to baseline levels approximately 3 to 4 years after relationship dissolution, as shown in Figure 3. Life satisfaction estimates at each measurement point are available in Appendix E.

To compare life satisfaction trajectories between groups, we used the best-fitting model (3i) to specify a multiple-group latent growth model. Adequate model fit was indicated by CFI (1.000), TLI (1.000), and RMSEA (<.001). We then conducted Wald tests on mean estimates for each latent parameter (see Table 5). Compared to the control group, the exposure group showed significantly greater declines in life satisfaction in the years surrounding relationship dissolution, and significantly greater long-term increases post-dissolution. However, the two groups did not differ significantly in baseline life satisfaction or pre-dissolution linear change.

Hypothesis 2: Size of Individual Differences in Life Satisfaction Trajectories

Hypothesis 2 predicted larger individual differences in change for the exposure group than the control group. Both groups showed significant individual differences across all latent parameters of life satisfaction, as shown in Table 6. To compare the size of these individual differences between groups, we conducted Wald tests on variance estimates for each latent parameter of the multiple-group model.

Table 6

Parameter Variance Estimates of the Best-Fitting Model for Life Satisfaction in the Exposure Group and Control Group (Model 3i)

	Exposure Group				Control Group				Difference	
Parameter	Variance	*SE*	*p*	95% CI	Variance	*SE*	*p*	95% CI	Wald	*p*
Intercept	0.262	0.038	<.001	[0.196, 0.345]	0.177	0.018	<.001	[0.144, 0.215]	4.24	.040
Linear Δ1	0.006	0.001	<.001	[0.004, 0.009]	0.003	0.001	<.001	[0.002, 0.005]	3.91	.048
Linear Δ2	0.020	0.003	<.001	[0.015, 0.026]	0.011	0.002	<.001	[0.008, 0.014]	8.51	.004
Linear Δ3	0.008	0.002	<.001	[0.005, 0.012]	0.010	0.001	<.001	[0.008, 0.013]	1.24	.265
Quadratic Δ3	0.000	0.000	<.001	[0.000, 0.000]	0.000	0.000	<.001	[0.000, 0.000]	0.00	.992

Note. CI = Credibility interval.

The exposure group showed larger individual differences in life satisfaction change than the control group before and during relationship dissolution (see Table 6). Furthermore, the exposure group showed greater heterogeneity in baseline life satisfaction. However, the size of individual differences in post-dissolution change did not differ significantly between groups. Taken together, these results partially support Hypothesis 2.

Hypotheses 3 and 4: Sources of Individual Differences in Life Satisfaction Trajectories

Hypotheses 3 and 4 predicted a negative association between change in life satisfaction before and after relationship dissolution, and significant moderating effects of demographic and psychosocial factors. The best-fitting model in both groups (3i) contained linear and quadratic growth parameters in the post-dissolution phase, which cannot be interpreted separately. However, given the limited sample size at the first and last measurement points (see Table 1), incorporating moderators of a quadratic growth parameter risks over-fitting a complex model to restricted data (Grimm et al., 2011). As such, we based our remaining analyses on the linear three-phase model (3h) to ensure that each phase of relationship dissolution had a single estimate of individual differences (e.g., van Scheppingen & Leopold, 2020). Model 3h had the third best fit out of the 22 models tested for the exposure group and the second best fit for control group.

To compare sources of individual differences in life satisfaction trajectories between groups, we specified a multiple-group conditional piecewise growth model with the following predictors of individual differences in intercepts and slopes: latent parameters (intercepts and slopes) of life satisfaction in preceding phases, re-partnering, having children, education, subjective income, social support, and perceived control. The regression coefficient estimates were found to be unreliable due to insufficient power. To address this, we limited measurement waves in the multiple-group model to those containing 250 or more participants per group. However, this still resulted in unreliable estimates. As group comparisons were not possible, we constructed separate conditional models for each group by adding predictors to Model 3h. Standardised regression coefficients are displayed in Table 7.

Table 7

Standardised Effects of Preceding Phases and Moderators on Life Satisfaction Trajectories for Model 3h

		Exposure Group				Control Group			
Outcome	Predictor	*β*	*SE*	*p*	95% CI	*β*	*SE*	*p*	95% CI
Intercept (Baseline)	Having children	−.33	.11	<.001	[−.55, −.14]	−.06	.09	.270	[−.26, .08]
	Education	−.16	.10	.055	[−.34, .06]	−.24	.06	<.001	[−.39, −.15]
	Subjective income	.00	.04	.461	[−.07, .08]	.01	.05	.478	[−.10, .08]
	Social support	.42	.06	<.001	[.25, .50]	.41	.05	<.001	[.32, .50]
	Perceived control	.32	.05	<.001	[.22, .41]	.39	.05	<.001	[.30, .49]
	Total R^2	**.573**	**.055**	**<.001**		**.493**	**.083**	**<.001**	
Linear Δ1 (Pre-dissolution)	Intercept	.30	.24	.124	[−.21, .73]	.17	.20	.175	[−.12, .56]
	R^2	**.320**	**.083**	**<.001**		**.179**	**.059**	**<.001**	
	Having children	.68	.28	.010	[.08, 1.11]	.07	.29	.390	[−.39, .65]
	Education	.33	.27	.112	[−.24, .82]	.77	.16	<.001	[.43, 1.02]
	Subjective income	.08	.06	.161	[−.05, .17]	.02	.11	.500	[−.09, .25]
	Social support	−.17	.16	.174	[−.35, 30]	.02	.19	.500	[−.35, .26]
	Perceived control	−.07	.12	.292	[−.25, .23]	.02	.20	.500	[−.38, .28]
	Total R^2	**.615**	**.247**	**<.001**		**.876**	**.239**	**<.001**	
Linear Δ2 (Dissolution)	Intercept	−1.10	.79	.144	[−1.76, 1.45]	−.80	.96	.379	[−1.55, 1.89]
	Linear Δ1	.72	1.47	.167	[−3.76, 2.09]	−.54	4.36	.500	[−16.04, 2.19]
	R^2	**.187**	**.047**	**<.001**		**.071**	**.050**	**<.001**	
	Having children	−.64	1.46	.174	[−2.06, 3.93]	.12	1.75	.408	[−5.73, 2.50]
	Education	−.23	.60	.328	[−1.37, 1.31]	.40	3.96	.500	[−2.34, 14.73]
	Subjective income	.04	.04	.134	[−.03, .12]	−.04	.04	.165	[−.12, .04]
	Social support	.47	.06	<.001	[.36, .58]	.53	.07	<.001	[.40, .68]
	Perceived control	.44	.06	<.001	[.32, .58]	.59	.08	<.001	[.44, .75]
	Total R^2	**.932**	**.064**	**<.001**		**.929**	**.065**	**<.001**	
Linear Δ3 (Post-dissolution)	Intercept	−1.49	.94	.133	[−2.26, 1.45]	−.96	.72	.209	[−1.47, 1.07]
	Linear Δ1	.73	1.73	.167	[−4.58, 2.20]	−.53	3.21	.500	[−11.74, 1.43]
	Linear Δ2	−1.32	.14	<.001	[−1.61, −1.07]	−.96	.11	<.001	[−1.19, −.77]
	R^2	**.139**	**.219**	**<.001**		**.226**	**.191**	**<.001**	
	Re-partnering	−.04	.06	.252	[−.16, .07]				
	Having children	−.66	1.72	.180	[−2.26, 4.77]	.14	1.30	.355	[−4.20, 1.92]
	Education	−.31	.69	.28	[−1.62, 1.41]	.42	2.93	.500	[−1.61, 10.74]
	Subjective income	.19	.05	<.001	[.09, .28]	−.01	.04	.348	[−.08, .06]
	Social support	.66	.08	<.001	[.51, .81]	.48	.05	<.001	[.39, .58]
	Perceived control	.52	.07	<.001	[.39, .66]	.51	.05	<.001	[.40, .61]
	Total R^2	**.597**	**.100**	**<.001**		**.441**	**.048**	**<.001**	

Note. CI = Credibility interval. R^2 values represent variance in life satisfaction trajectories accounted for by preceding growth parameters, whereas Total R^2 values represent variance accounted for by preceding growth parameters plus demographic and psychosocial factors.

For the exposure group, results indicate a large negative association between linear change in life satisfaction during and after relationship dissolution ($\beta = -1.32$, $p < .001$). Specifically, women who experienced sharper declines in the years surrounding relationship dissolution showed stronger long-term increases after the event. This effect was also significant for the control group. All other effects of life satisfaction change in preceding phases of dissolution were non-significant. These results partially support Hypothesis 3.

In the exposure group, the total variance explained by demographic and psychosocial factors, over and above life satisfaction in preceding phases, ranged from 29.5% to 74.5% (pre-dissolution and dissolution slopes, respectively). Baseline life satisfaction was negatively associated with having children, and positively associated with social support and perceived control. The pre-dissolution life satisfaction slope was positively moderated by having children. The dissolution slope was positively moderated by social support and perceived control. The post-dissolution slope was positively moderated by subjective income ($\beta = .19$, $p < .001$) and, to a larger degree, social support ($\beta = .66$, $p < .001$) and perceived control ($\beta = .52$, $p < .001$). No significant moderating effects were observed in the exposure group for education or re-partnering. These results provide partial support for Hypothesis 4.

For the control group, baseline life satisfaction was negatively associated with education, and positively associated with social support and perceived control. The pre-dissolution slope was positively moderated by education. The dissolution and post-dissolution slopes were positively moderated by social support and perceived control. No significant moderating effects of subjective income or having children were observed for the control group.

Discussion

The present study investigated life satisfaction trajectories and protective factors for Australian women around relationship dissolution in later life. We drew on a propensity-matching and piecewise growth modelling approach used in past research (van Scheppingen & Leopold, 2020), observing much longer time periods surrounding dissolution. We incorporated a wider range of demographic and psychosocial moderators of change, some of which were time-varying. As such, this study provided a clearer indication of why some women adjust to relationship dissolution better than others.

Mean-Level Change in Life Satisfaction

Our first aim was to investigate mean-level life satisfaction trajectories in middle-aged Australian women before and after relationship dissolution. Like van Scheppingen and Leopold (2020), we found that the average life satisfaction trajectory for divorced and separated women was characterised by three distinct phases: pre-dissolution, dissolution, and post-dissolution. We found stable long-term life satisfaction before relationship dissolution, a sudden decline in the years surrounding the event, and long-term gradual curvilinear increases in the years after dissolution. Our results correspond with previous longitudinal research, which indicates that relationship dissolution encompasses gradual and sudden changes in life satisfaction, including anticipatory declines in the years preceding the event (Asselmann & Specht, 2023; Denissen et al., 2019; Doré & Bolger, 2018; Lucas, 2005; Luhmann et al., 2012).

As we observed life satisfaction trajectories over a much longer period, and with less frequent measurements, the stable pre-event slope in our results likely preceded any anticipatory declines in life satisfaction, which van Scheppingen and Leopold (2020) captured in their negative pre-divorce slope. In addition, our finding that long-term life satisfaction before dissolution remained stable contrasts with research using German panel data, which found gradual declines in life satisfaction during the 20 years before divorce (Doré & Bolger, 2018).

Furthermore, we found that divorced and separated women recovered to their pre-dissolution levels of life satisfaction approximately 3 to 4 years after the event. This finding contrasts with longitudinal studies using German panel data, which showed incomplete recovery of pre-divorce life satisfaction 5 to 6 years after the event (Doré & Bolger, 2018; Lucas, 2005; van Scheppingen & Leopold, 2020). In line with the crisis model (Amato, 2000), our results suggest that the wellbeing impact of relationship dissolution is temporary and dependent on an individual's resources. Although we found significant individual differences in life satisfaction trajectories, women generally regained their pre-event levels of life satisfaction.

Association Between Relationship Dissolution and Life Satisfaction

Our second aim was to disentangle the effects of relationship dissolution from other normative changes in life satisfaction. For women who remained married or partnered, our results indicated stability and slight increases in life satisfaction across the observation period. This suggests that the declines in life satisfaction experienced by divorced and separated women are at least partly attributed to the relationship dissolution process. This finding was strengthened by the propensity-score matching employed to minimise selection effects. Notably, we matched women on mental health, unlike previous studies (Anusic et al., 2014; van Scheppingen & Leopold, 2020).

In contrast to previous studies containing control groups (Lucas, 2005; van Scheppingen & Leopold, 2020), we found that life satisfaction levels for the divorced and separated women overtook those of the married and partnered women approximately 4.5 years after relationship dissolution. This finding could be explained by theories of post-traumatic growth, whereby individuals who experience major crises may develop increased insight and gratitude regarding their circumstances, which in turn, increases their subjective wellbeing (Jayawickreme et al., 2021; Tedeschi & Calhoun, 2004).

We also found that divorced and separated women displayed significantly larger individual differences in trajectories than their married and partnered counterparts before and during relationship dissolution. This finding differed from van Scheppingen and Leopold (2020), who found larger individual differences in life satisfaction change among divorcees during and after the event. The larger individual differences in change before dissolution could reflect the heterogeneity of the relationship breakdown process (Amato & Hohmann-Marriott, 2007).

Individual Differences in Life Satisfaction Trajectories

Our third aim was to explain sources of individual differences in life satisfaction trajectories surrounding relationship dissolution. In line with van Scheppingen and Leopold (2020), we found that change in life satisfaction during relationship dissolution was negatively associated with change after the event. Specifically, women whose life satisfaction decreased in the years surrounding dissolution experienced greater long-term increases thereafter. One explanation could be that women who had high levels of stress and conflict during their relationship may have felt relieved to transition out of it (Amato & Hohmann-Marriott, 2007; Wheaton, 1990). However, given that this association was also observed for the matched controls, it may also represent day-to-day fluctuations in life satisfaction or marital problems which people eventually managed to solve (van Scheppingen & Leopold, 2020).

Psychosocial and demographic factors explained between 29.5% and 74.5% of the variance in life satisfaction trajectories, over and above change in preceding phases of relationship dissolution. Specifically, we found significant positive moderating effects of social support, perceived control, and subjective income. Women with high levels of social support and perceived control reported higher baseline life satisfaction. Furthermore, social support and perceived control were found to be protective against declines in life satisfaction during relationship dissolution, and predictive of greater long-term increases after the event.

Our findings on the moderating effects of social support align with Yu and Liu (2021), who found social support to positively moderate depression trajectories around stressful life events, including divorce, in older adults. In addition, the observed moderating effects of perceived control on life satisfaction trajectories are in line with similar findings for other major life events, such as unemployment (Infurna et al., 2016). This combined evidence suggests that interventions to promote social support and perceived control could benefit individuals experiencing relationship dissolution. Furthermore, similar results were also observed for the control group, suggesting that such interventions could support middle-aged women universally. Indeed, British longitudinal research showed that psychosocial factors, including social support and control, had the largest influence on quality-of-life trajectories in old age, as opposed to demographic factors (Zaninotto et al., 2009).

Furthermore, we found that women with higher subjective income experienced greater long-term increases in life satisfaction after relationship dissolution. Moreover, subjective income did not moderate life satisfaction trajectories for similar married and partnered women. By demonstrating this effect longitudinally, using a propensity-matched control group, the present study adds to the limited evidence for income moderating post-divorce wellbeing (Booth & Amato, 1991; Garvin et al., 1993; Shapiro, 1996).

The effects of other explanatory factors – re-partnering, having children, and education – were either non-significant or unexpected. Previous longitudinal research has shown that re-partnering improves life satisfaction trajectories post-divorce (Gloor et al., 2021; Lucas, 2005). However, this was not demonstrated in the present study. Future scholarship could examine whether individuals potentially experience the countervailing effects of a new partnership bringing social and economic benefits, but also difficulties in navigating a new familial structure.

Although mothers reported lower baseline life satisfaction and experienced less pronounced pre-dissolution declines than women without children, unexpectedly, no significant moderating effects of having children were observed after relationship dissolution. This finding is partially in line with van Scheppingen and Leopold (2020), who also found that having children did not exacerbate the effects of divorce.

We found that education only moderated life satisfaction trajectories for women who remained married or partnered. Specifically, more highly educated individuals had lower life satisfaction at baseline, but experienced greater increases in life satisfaction over the following 20 years. Previous literature has attributed the former effect to higher life expectations held by highly educated individuals (Kristoffersen, 2018). The latter effect reflects recent meta-analytic work showing a small, positive association between education and subjective wellbeing (Tan et al., 2020). The fact that education did not significantly moderate life satisfaction trajectories for divorced and separated women suggests that the effects of relationship dissolution could be felt across the boundaries of SES. However, these results should be interpreted with caution as we had collapsed education into a binary variable (i.e., high school or lower vs further study) to ensure convergence of the conditional models.

Consistent with the divorce-stress-adjustment perspective (Amato, 2000), the present study has identified social support, perceived control, and subjective income as individual and interpersonal resources, explaining substantial variance in life satisfaction outcomes. In this way, we have provided valuable insight into the application of divorce adjustment theory for older adults. Within the restraints of our conditional models, these protective factors were examined using average values at each phase of relationship dissolution. Future research could confirm our findings by incorporating social support, perceived control, and subjective income as fully time-varying moderators.

Limitations and Future Directions

The present study used ALSWH data to follow a large sample of Australian women throughout middle age. We compared divorced and separated women with propensity-matched controls to examine the association between relationship dissolution and life satisfaction. A strength of the present study beyond existing literature was to investigate additional time-varying psychosocial moderators of life satisfaction trajectories to inform wellbeing interventions. However, our results should be interpreted with respect to limitations of the dataset and analysis.

First, as ALSWH data were collected in three-yearly intervals, our study lacked the sensitivity to capture fine-grained life satisfaction change, particularly in the years surrounding relationship dissolution. This may have impacted estimates of life satisfaction change during dissolution and when women regained pre-event life satisfaction levels. Future research in the Australian context would benefit from using panel data with more frequent measurement waves, such as the Household, Income and Labour Dynamics in Australia (HILDA) survey (Watson & Wooden, 2012).

Second, the life satisfaction measure from the ALSWH was evaluated by some respondents as limited in its domains and response options (ALSWH, 1996). Specifically, the 'partner/closest personal relationship' domain was not relevant to some women and there was no neutral satisfaction option available. However, a strength of the measure was its multi-item nature, which allowed for more precise examination of individual differences (van Scheppingen & Leopold, 2020).

Third, due to attrition, the ALSWH sample became less representative of the Australian population as time went on, limiting the external validity of our findings.

Specifically, ALSWH respondents were more highly educated, more highly paid, more likely to be married and more likely to come from an English-speaking background than the general Australian population (Powers, 2004). Unlike in the HILDA survey, a strength of not supplementing the initial sample of ALSWH respondents is that more measurement points were available for each individual, allowing for our complex analysis involving piecewise growth modelling. Future research should investigate life satisfaction trajectories of women in racial, sexual, and socioeconomic minority groups to ensure the design of appropriate interventions.

Lastly, direct between-group comparisons of moderators of life satisfaction trajectories were not possible due to insufficient power. Specifically, the complexity of the multiple-group conditional piecewise model required a larger sample size than was available to produce reliable regression coefficient estimates. Therefore, conclusions about whether the moderating effects of demographic and psychosocial factors are attributed to relationship dissolution should be made with caution. Future work on individual differences in life satisfaction trajectories would benefit from using larger samples with more measurement points for each participant to enable group comparisons.

The present study identified social support and perceived control to have the greatest impact on long-term adjustment to relationship dissolution in middle-aged women. It would be of interest to examine pathways for suitable interventions targeting these psychosocial factors in middle-aged women. Previous literature on anxiety disorders indicates that cognitive behaviour therapy (CBT) can promote higher levels of perceived control (Gallagher et al., 2014). As such, future research could examine whether CBT improves subjective wellbeing through targeting perceived control. As longitudinal research on quality-of-life in older age has highlighted that increasing social support can protect against wellbeing declines

(Zaninotto, 2009), further research on identifying appropriate support programs would be beneficial.

Furthermore, a review by Lin and Brown (2020) highlighted that future scholarship could examine whether adjustment to later-life relationship dissolution is moderated by turning points specific to older adults, such as becoming an empty nester, retiring, or experiencing health decline. The ALSWH would be well-suited to this line of research as it contains life transition variables tailored for women in this age group.

Conclusion

Our prospective longitudinal study examined long-term life satisfaction trajectories around later-life relationship dissolution in Australian women. Divorced and separated women experienced stable life satisfaction in the years before dissolution, a sudden decline in the years surrounding the event, and gradual long-term increases thereafter, exceeding their baseline levels. The matched control group of married or partnered women showed a stable and slightly increasing life satisfaction trajectory throughout the study period. This suggests that any declines in life satisfaction were at least partly associated with relationship dissolution. Psychosocial and demographic factors explained a moderate to large amount of variance in life satisfaction trajectories. Importantly, social support, perceived control, and subjective income emerged as protective factors for women’s adjustment to relationship dissolution. These findings offer valuable insight into wellbeing trends which will inform much-needed interventions for older Australian women recovering from separation and divorce.

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Appendix A

Description of Measures Used for Propensity-Score Matching Only

Mental Health and Physical Health

Mental health and physical health were assessed using the Mental and Physical Component Scores (MCS and PCS, respectively) from the Short Form 36 Survey (SF-36; Ware et al., 1994). MCS values are derived from the vitality, social functioning, role emotional, and mental health scales from the SF-36. PCS values are derived from the physical functioning, role physical, bodily pain, and general health scales. MCS and PCS values are standardised as *T* scores (mean = 50, standard deviation = 10).

Language Spoken at Home

Language spoken at home was assessed in Wave 1 and contained five response options (i.e., “English, Australia,” “English, Other,” “European,” “Asian,” and “Other”; ALSWH, 2020a). For propensity-score matching, we collapsed these options into two categories: *English* and *Other*.

Location

Location was assessed in all waves and contained four response options (i.e., “Major cities of Australia,” “Inner regional Australia,” “Outer regional Australia,” and “Remote and very remote Australia”; ALSWH, 2020a). For propensity-score matching, we collapsed these options into three categories: *Urban*, *Regional* and *Remote*.

Age

Respondents in the 1946-51 birth cohort were aged 45 – 50 years in Wave 1 and reported their age in the Wave 1 survey (ALSWH, 2020a). Age was treated as a categorical variable with six levels (i.e., one for each age in years).

Employment

Employment was assessed in all waves by hours worked per week. There were five response options (i.e., "Not working," "1 – 24 hours," "25 – 34 hours," "35 – 48 hours," and "49+ hours").

Housing Situation

Housing situation was assessed in Waves 1, 2, 8, and 9 by type of dwelling (ALSWH, 2020a). There were four response options (i.e., "House," "Flat/unit/apartment," "Caravan/tent," and "Other"). For propensity-score matching, we collapsed the "Caravan/tent" and "Other" categories.

Home Ownership

Home ownership was assessed in Waves 1, 2, 8, and 9 with a single item, "*in whose name is the ownership/purchasing agreement/tenancy agreement"* (ALSWH, 2020a). For propensity-score matching, we collapsed the response options (i.e., "Self," "Partner/spouse," "Partner and self," "Parents or family," and "Self and others") into three categories: *Self, Partner, Partner and self,* and *Others.*

Appendix B

Specifications for 22 Unconditional Models of Life Satisfaction

<table>
<tr><th colspan="2">Mplus ‘ANALYSIS’ command input for all 22 unconditional models</th></tr>
<tr><td colspan="2">PROCESSORS = 12;
COVERAGE = .001;
TYPE = RANDOM;
ESTIMATOR = BAYES;
FBITERATIONS = 60000;
CHAINS = 6;</td></tr>
<tr><th colspan="2">One-phase models</th></tr>
<tr><th>Model specifications</th><th>Slope equations</th></tr>
<tr><td>Model 1a
(no change, intercept only)

i | y_8@0 y_7@1 y_6@2 y_5@3 y_4@4 y_3@5 y_2@6 y_1@7 y0@8 y1@9 y2@10 y3@11 y4@12 y5@13 y6@14 y7@15 y8@16;

!Estimate means
[i] (ix);</td><td>Phase 1:
py_8 = ix;
py_7 = ix;
py_6 = ix;
py_5 = ix;
py_4 = ix;
py_3 = ix;
py_2 = ix;
py_1 = ix;
py0 = ix;
py1 = ix;
py2 = ix;
py3 = ix;
py4 = ix;
py5 = ix;
py6 = ix;
py7 = ix;
py8 = ix;</td></tr>
<tr><td>Model 1b
(linear change)

i s1 | y_8@0 y_7@1 y_6@2 y_5@3 y_4@4 y_3@5 y_2@6 y_1@7 y0@8 y1@9 y2@10 y3@11 y4@12 y5@13 y6@14 y7@15 y8@16;

!Estimate means
[i] (ix);
[s1] (s1x);</td><td>Phase 1:
py_8 = ix + s1x*0;
py_7 = ix + s1x*1;
py_6 = ix + s1x*2;
py_5 = ix + s1x*3;
py_4 = ix + s1x*4;
py_3 = ix + s1x*5;
py_2 = ix + s1x*6;
py_1 = ix + s1x*7;
py0 = ix + s1x*8;
py1 = ix + s1x*9;
py2 = ix + s1x*10;
py3 = ix + s1x*11;
py4 = ix + s1x*12;
py5 = ix + s1x*13;
py6 = ix + s1x*14;
py7 = ix + s1x*15;
py8 = ix + s1x*16;</td></tr>
<tr><td>Model 1c
(quadratic change)

i s1 sq1 | y_8@0 y_7@1 y_6@2 y_5@3 y_4@4 y_3@5 y_2@6 y_1@7 y0@8 y1@9 y2@10 y3@11 y4@12 y5@13 y6@14 y7@15 y8@16;

!Estimate means
[i] (ix);
[s1] (s1x);
[sq1] (sq1x);</td><td>Phase 1:
py_8 = ix + s1x*0 + (0^2)*sq1x;
py_7 = ix + s1x*1 + (1^2)*sq1x;
py_6 = ix + s1x*2 + (2^2)*sq1x;
py_5 = ix + s1x*3 + (3^2)*sq1x;
py_4 = ix + s1x*4 + (4^2)*sq1x;
py_3 = ix + s1x*5 + (5^2)*sq1x;
py_2 = ix + s1x*6 + (6^2)*sq1x;
py_1 = ix + s1x*7 + (7^2)*sq1x;
py0 = ix + s1x*8 + (8^2)*sq1x;
py1 = ix + s1x*9 + (9^2)*sq1x;
py2 = ix + s1x*10 + (10^2)*sq1x;</td></tr>
</table>

	py3 = ix + s1x*11 + (11^2)*sq1x;
	py4 = ix + s1x*12 + (12^2)*sq1x;
	py5 = ix + s1x*13 + (13^2)*sq1x;
	py6 = ix + s1x*14 + (14^2)*sq1x;
	py7 = ix + s1x*15 + (15^2)*sq1x;
	py8 = ix + s1x*16 + (16^2)*sq1x;

Two-phase models

Model specifications	Slope equations	

Model 2a
(gradual linear + no change)
 	
i s1 | y_8@0 y_7@1 y_6@2 y_5@3 y_4@4 y_3@5 y_2@6 y_1@7 y0@7 y1@7 y2@7 y3@7 y4@7 y5@7 y6@7 y7@7 y8@7;
 	
i s2| y_8@0 y_7@0 y_6@0 y_5@0 y_4@0 y_3@0 y_2@0 y_1@0 y0@1 y1@2 y2@3 y3@4 y4@5 y5@6 y6@7 y7@8 y8@9;
 	
!Estimate means
[i] (ix);
[s1] (s1x);
[s2@0];
s2@0;
	Phase 1:
	py_8 = ix + s1x*0;
	py_7 = ix + s1x*1;
	py_6 = ix + s1x*2;
	py_5 = ix + s1x*3;
	py_4 = ix + s1x*4;
	py_3 = ix + s1x*5;
	py_2 = ix + s1x*6;
	py_1 = ix + s1x*7;
		Phase 2:
		py0 = ix;
		py1 = ix;
		py2 = ix;
		py3 = ix;
		py4 = ix;
		py5 = ix;
		py6 = ix;
		py7 = ix;
		py8 = ix;

Model 2b
(gradual linear + gradual linear)
 	
i s1 | y_8@0 y_7@1 y_6@2 y_5@3 y_4@4 y_3@5 y_2@6 y_1@7 y0@7 y1@7 y2@7 y3@7 y4@7 y5@7 y6@7 y7@7 y8@7;
 	
i s2| y_8@0 y_7@0 y_6@0 y_5@0 y_4@0 y_3@0 y_2@0 y_1@0 y0@1 y1@2 y2@3 y3@4 y4@5 y5@6 y6@7 y7@8 y8@9;
 	
!Estimate means
[i] (ix);
[s1] (s1x);
[s2] (s2x);
	Phase 1:
	py_8 = ix + s1x*0;
	py_7 = ix + s1x*1;
	py_6 = ix + s1x*2;
	py_5 = ix + s1x*3;
	py_4 = ix + s1x*4;
	py_3 = ix + s1x*5;
	py_2 = ix + s1x*6;
	py_1 = ix + s1x*7;
		Phase 2:
		py0 = ix + s2x*1;
		py1 = ix + s2x*2;
		py2 = ix + s2x*3;
		py3 = ix + s2x*4;
		py4 = ix + s2x*5;
		py5 = ix + s2x*6;
		py6 = ix + s2x*7;
		py7 = ix + s2x*8;
		py8 = ix + s2x*9;

Model 2c
(gradual linear + gradual quadratic)
 	
i s1 | y_8@0 y_7@1 y_6@2 y_5@3 y_4@4 y_3@5 y_2@6 y_1@7 y0@7 y1@7 y2@7 y3@7 y4@7 y5@7 y6@7 y7@7 y8@7;
 	
i s2 sq2 | y_8@0 y_7@0 y_6@0 y_5@0 y_4@0 y_3@0 y_2@0 y_1@0 y0@0 y1@1 y2@2 y3@3 y4@4 y5@5 y6@6 y7@7 y8@8;
 	
!Estimate means
[i] (ix);
[s1] (s1x);
[s2] (s2x);
[sq2] (sq2x);
	Phase 1:
	py_8 = ix + s1x*0;
	py_7 = ix + s1x*1;
	py_6 = ix + s1x*2;
	py_5 = ix + s1x*3;
	py_4 = ix + s1x*4;
	py_3 = ix + s1x*5;
	py_2 = ix + s1x*6;
	py_1 = ix + s1x*7;
		Phase 2:
		py0 = ix + s2x*1 + (1^2)*sq2x;
		py1 = ix + s2x*2 + (2^2)*sq2x;
		py2 = ix + s2x*3 + (3^2)*sq2x;
		py3 = ix + s2x*4 + (4^2)*sq2x;
		py4 = ix + s2x*5 + (5^2)*sq2x;
		py5 = ix + s2x*6 + (6^2)*sq2x;
		py6 = ix + s2x*7 + (7^2)*sq2x;
		py7 = ix + s2x*8 + (8^2)*sq2x;
		py8 = ix + s2x*9 + (9^2)*sq2x;

Model 2d
(no change + gradual linear)
 	
i | y_8@0 y_7@1 y_6@2 y_5@3 y_4@4 y_3@5 y_2@6 y_1@7 y0@7 y1@7 y2@7
	Phase 1:
	py_8 = ix;
	py_7 = ix;
	py_6 = ix;
	py_5 = ix;
		Phase 2:
		py0 = ix + s2x*1;
		py1 = ix + s2x*2;
		py2 = ix + s2x*3;
		py3 = ix + s2x*4;

y3@7 y4@7 y5@7 y6@7 y7@7 y8@7;
 	
i s2 | y_8@0 y_7@0 y_6@0 y_5@0 y_4@0
y_3@0 y_2@0 y_1@0 y0@1 y1@2 y2@3
y3@4 y4@5 y5@6 y6@7 y7@8 y8@9;
 	
!Estimate means
[i] (ix);
[s2] (s2x);
	py_4 = ix;
	py_3 = ix;
	py_2 = ix;
	py_1 = ix;
		py4 = ix + s2x*5;
		py5 = ix + s2x*6;
		py6 = ix + s2x*7;
		py7 = ix + s2x*8;
		py8 = ix + s2x*9;

Model 2e
(no change + gradual quadratic)
 	
i | y_8@0 y_7@1 y_6@2 y_5@3 y_4@4
y_3@5 y_2@6 y_1@7 y0@7 y1@7 y2@7
y3@7 y4@7 y5@7 y6@7 y7@7 y8@7;
 	
i s2 sq2 | y_8@0 y_7@0 y_6@0 y_5@0 y_4@0
y_3@0 y_2@0 y_1@0y0@1 y1@2 y2@3 y3@4
y4@5 y5@6 y6@7 y7@8 y8@9;
 	
!Estimate means
[i] (ix);
[s2] (s2x);
[sq2] (sq2x);
	Phase 1:
	py_8 = ix;
	py_7 = ix;
	py_6 = ix;
	py_5 = ix;
	py_4 = ix;
	py_3 = ix;
	py_2 = ix;
	py_1 = ix;
		Phase 2:
		py0 = ix + s2x*1 + (1^2)*sq2x;
		py1 = ix + s2x*2 + (2^2)*sq2x;
		py2 = ix + s2x*3 + (3^2)*sq2x;
		py3 = ix + s2x*4 + (4^2)*sq2x;
		py4 = ix + s2x*5 + (5^2)*sq2x;
		py5 = ix + s2x*6 + (6^2)*sq2x;
		py6 = ix + s2x*7 + (7^2)*sq2x;
		py7 = ix + s2x*8 + (8^2)*sq2x;
		py8 = ix + s2x*9 + (9^2)*sq2x;

Model 2f
(gradual quadratic + gradual quadratic)
 	
i s1 sq1 | y_8@0 y_7@1 y_6@2 y_5@3 y_4@4
y_3@5 y_2@6 y_1@7 y0@7 y1@7 y2@7
y3@7 y4@7 y5@7 y6@7 y7@7 y8@7;
 	
i s2 sq2 | y_8@0 y_7@0 y_6@0 y_5@0 y_4@0
y_3@0 y_2@0 y_1@0 y0@1 y1@2 y2@3
y3@4 y4@5 y5@6 y6@7 y7@8 y8@9;
 	
!Estimate means
[i] (ix);
[s1] (s1x);
[sq1] (sq1x);
[s2] (s2x);
[sq2] (sq2x);
	Phase 1:
	py_8 = ix + s1x*0 + (0^2)*sq1x;
	py_7 = ix + s1x*1 + (1^2)*sq1x;
	py_6 = ix + s1x*2 + (2^2)*sq1x;
	py_5 = ix + s1x*3 + (3^2)*sq1x;
	py_4 = ix + s1x*4 + (4^2)*sq1x;
	py_3 = ix + s1x*5 + (5^2)*sq1x;
	py_2 = ix + s1x*6 + (6^2)*sq1x;
	py_1 = ix + s1x*7 + (7^2)*sq1x;
		Phase 2:
		py0 = ix + s2x*1 + (1^2)*sq2x;
		py1 = ix + s2x*2 + (2^2)*sq2x;
		py2 = ix + s2x*3 + (3^2)*sq2x;
		py3 = ix + s2x*4 + (4^2)*sq2x;
		py4 = ix + s2x*5 + (5^2)*sq2x;
		py5 = ix + s2x*6 + (6^2)*sq2x;
		py6 = ix + s2x*7 + (7^2)*sq2x;
		py7 = ix + s2x*8 + (8^2)*sq2x;
		py8 = ix + s2x*9 + (9^2)*sq2x;

Model 2g
(gradual quadratic + gradual linear)
 	
i s1 sq1 | y_8@0 y_7@1 y_6@2 y_5@3 y_4@4
y_3@5 y_2@6 y_1@7 y0@7 y1@7 y2@7
y3@7 y4@7 y5@7 y6@7 y7@7 y8@7;
 	
i s2 | y_8@0 y_7@0 y_6@0 y_5@0 y_4@0
y_3@0 y_2@0 y_1@0 y0@1 y1@2 y2@3
y3@4 y4@5 y5@6 y6@7 y7@8 y8@9;
 	
!Estimate means
[i] (ix);
[s1] (s1x);
[sq1] (sq1x);
[s2] (s2x);
	Phase 1:
	py_8 = ix + s1x*0 + (0^2)*sq1x;
	py_7 = ix + s1x*1 + (1^2)*sq1x;
	py_6 = ix + s1x*2 + (2^2)*sq1x;
	py_5 = ix + s1x*3 + (3^2)*sq1x;
	py_4 = ix + s1x*4 + (4^2)*sq1x;
	py_3 = ix + s1x*5 + (5^2)*sq1x;
	py_2 = ix + s1x*6 + (6^2)*sq1x;
	py_1 = ix + s1x*7 + (7^2)*sq1x;
		Phase 2:
		py0 = ix + s2x*1;
		py1 = ix + s2x*2;
		py2 = ix + s2x*3;
		py3 = ix + s2x*4;
		py4 = ix + s2x*5;
		py5 = ix + s2x*6;
		py6 = ix + s2x*7;
		py7 = ix + s2x*8;
		py8 = ix + s2x*9;

Model 2h
(gradual quadratic + no change)
 	
i s1 sq1 | y_8@0 y_7@1 y_6@2 y_5@3 y_4@4
	Phase 1:
	py_8 = ix + s1x*0 + (0^2)*sq1x;
	py_7 = ix + s1x*1 + (1^2)*sq1x;
	py_6 = ix + s1x*2 + (2^2)*sq1x;
		Phase 2:
		py0 = ix;
		py1 = ix;
		py2 = ix;

y_3@5 y_2@6 y_1@7 y0@7 y1@7 y2@7	py_5 = ix + s1x*3 + (3^2)*sq1x;	py3 = ix;
y3@7 y4@7 y5@7 y6@7 y7@7 y8@7;	py_4 = ix + s1x*4 + (4^2)*sq1x;	py4 = ix;
	py_3 = ix + s1x*5 + (5^2)*sq1x;	py5 = ix;
i s2 | y_8@0 y_7@0 y_6@0 y_5@0 y_4@0	py_2 = ix + s1x*6 + (6^2)*sq1x;	py6 = ix;
y_3@0 y_2@0 y_1@0 y0@1 y1@2 y2@3	py_1 = ix + s1x*7 + (7^2)*sq1x;	py7 = ix;
y3@4 y4@5 y5@6 y6@7 y7@8 y8@9;		py8 = ix;
!Estimate means		
[i] (ix);		
[s1] (s1x);		
[sq1] (sq1x);		
[s2@0];		
s2@0;		

Three-phase models

Model 3a (no change + sudden change + no change)

!Factor loadings
i | y_8@0 y_7@1 y_6@2 y_5@3 y_4@4 y_3@5 y_2@6 y_1@6 y0@6 y1@6 y2@6 y3@6 y4@6 y5@6 y6@6 y7@6 y8@6;

i s2 | y_8@0 y_7@0 y_6@0 y_5@0 y_4@0 y_3@0 y_2@0 y_1@1 y0@2 y1@2 y2@2 y3@2 y4@2 y5@2 y6@2 y7@2 y8@2;

i | y_8@0 y_7@0 y_6@0 y_5@0 y_4@0 y_3@0 y_2@0 y_1@0 y0@0 y1@1 y2@2 y3@3 y4@4 y5@5 y6@6 y7@7 y8@8;

!Estimate means
[i] (ix);
[s2] (s2x);

!Slope equations

Phase 1:	Phase 2:	Phase 3:
py_8 = ix;	py_1 = ix + s2x*1;	py1 = ix;
py_7 = ix;	py0 = ix + s2x*2;	py2 = ix;
py_6 = ix;		py3 = ix;
py_5 = ix;		py4 = ix;
py_4 = ix;		py5 = ix;
py_3 = ix;		py6 = ix;
py_2 = ix;		py7 = ix;
		py8 = ix;

Model 3b (gradual linear 1 + sudden + gradual linear 1)

!Factor loadings:
i s1 | y_8@0 y_7@1 y_6@2 y_5@3 y_4@4 y_3@5 y_2@6 y_1@6 y0@6 y1@6 y2@6 y3@6 y4@6 y5@6 y6@6 y7@6 y8@6;

i s2 | y_8@0 y_7@0 y_6@0 y_5@0 y_4@0 y_3@0 y_2@0 y_1@1 y0@2 y1@2 y2@2 y3@2 y4@2 y5@2 y6@2 y7@2 y8@2;

i s3 | y_8@0 y_7@0 y_6@0 y_5@0 y_4@0 y_3@0 y_2@0 y_1@0 y0@0 y1@1 y2@2 y3@3 y4@4 y5@5 y6@6 y7@7 y8@8;

!Estimate means
[i] (ix);
[s1] (s1x);
[s2] (s2x);
[s3] (s3x);
s1 (vs1x);
s3 (vs3x);

!Slope equations

Phase 1:	Phase 2:	Phase 3:
py_8 = ix + s1x*0;	py_1 = ix + s2x*1;	py1 = ix + s3x*1;
py_7 = ix + s1x*1;	py0 = ix + s2x*2;	py2 = ix + s3x*2;
py_6 = ix + s1x*2;		py3 = ix + s3x*3;
py_5 = ix + s1x*3;		py4 = ix + s3x*4;
py_4 = ix + s1x*4;		py5 = ix + s3x*5;
py_3 = ix + s1x*5;		py6 = ix + s3x*6;
py_2 = ix + s1x*6;		py7 = ix + s3x*7;
		py8 = ix + s3x*8;

Model 3c (gradual quadratic 1 + sudden + gradual quadratic 1)

```
!Factor loadings
i s1 sq1 | y_8@0 y_7@1 y_6@2 y_5@3 y_4@4 y_3@5 y_2@6 y_1@6 y0@6 y1@6 y2@6 y3@6 y4@6 y5@6 y6@6 y7@6 y8@6;

i s2 | y_8@0 y_7@0 y_6@0 y_5@0 y_4@0 y_3@0 y_2@0 y_1@1 y0@2 y1@2 y2@2 y3@2 y4@2 y5@2 y6@2 y7@2 y8@2;

i s3 sq3 | y_8@0 y_7@0 y_6@0 y_5@0 y_4@0 y_3@0 y_2@0 y_1@0 y0@0 y1@1 y2@2 y3@3 y4@4 y5@5 y6@6 y7@7 y8@8;

!Estimate means
   [i] (ix);
   [s1] (s1x);
   [sq1] (sq1x);
   [s2] (s2x);
   [s3] (s3x);
   [sq3] (sq3x);
s1 (vs1x);
s3 (vs3x);
sq1 (vsq1x);
sq3 (vsq3x);
s1x = s3x;
sq1x = sq3x;
vs1x = vs3x;
vsq1x = vsq3x;

!Slope equations
Phase 1:
py_8 = ix + s1x*0 + (0^2)*sq1x;
py_7 = ix + s1x*1 + (1^2)*sq1x;
py_6 = ix + s1x*2 + (2^2)*sq1x;
py_5 = ix + s1x*3 + (3^2)*sq1x;
py_4 = ix + s1x*4 + (4^2)*sq1x;
py_3 = ix + s1x*5 + (5^2)*sq1x;
py_2 = ix + s1x*6 + (6^2)*sq1x;
Phase 2:
py_1 = ix + s2x*1;
py0  = ix + s2x*2;
Phase 3:
py1  = ix + s3x*1 + (1^2)*sq3x;
py2  = ix + s3x*2 + (2^2)*sq3x;
py3  = ix + s3x*3 + (3^2)*sq3x;
py4  = ix + s3x*4 + (4^2)*sq3x;
py5  = ix + s3x*5 + (5^2)*sq3x;
py6  = ix + s3x*6 + (6^2)*sq3x;
py7  = ix + s3x*7 + (7^2)*sq3x;
py8  = ix + s3x*8 + (8^2)*sq3x;
```

Model 3d (no change + sudden + gradual linear)

```
!Factor loadings
i | y_8@0 y_7@1 y_6@2 y_5@3 y_4@4 y_3@5 y_2@6 y_1@6 y0@6 y1@6 y2@6 y3@6 y4@6 y5@6 y6@6 y7@6 y8@6;

i s2 | y_8@0 y_7@0 y_6@0 y_5@0 y_4@0 y_3@0 y_2@0 y_1@1 y0@2 y1@2 y2@2 y3@2 y4@2 y5@2 y6@2 y7@2 y8@2;

i s3 | y_8@0 y_7@0 y_6@0 y_5@0 y_4@0 y_3@0 y_2@0 y_1@0 y0@0 y1@1 y2@2 y3@3 y4@4 y5@5 y6@6 y7@7 y8@8;

!Estimate means
   [i] (ix);
   [s2] (s2x);
   [s3] (s3x)

!Slope equations
Phase 1:
py_8 = ix;
py_7 = ix;
py_6 = ix;
py_5 = ix;
py_4 = ix;
py_3 = ix;
py_2 = ix;
Phase 2:
py_1 = ix + s2x*1;
py0  = ix + s2x*2;
Phase 3:
py1  = ix + s3x*1;
py2  = ix + s3x*2;
py3  = ix + s3x*3;
py4  = ix + s3x*4;
py5  = ix + s3x*5;
py6  = ix + s3x*6;
py7  = ix + s3x*7;
py8  = ix + s3x*8;
```

Model 3e (no change + sudden + gradual quadratic)

```
!Factor loadings
i | y_8@0 y_7@1 y_6@2 y_5@3 y_4@4 y_3@5 y_2@6 y_1@6 y0@6 y1@6 y2@6 y3@6 y4@6 y5@6 y6@6 y7@6 y8@6;

i s2 | y_8@0 y_7@0 y_6@0 y_5@0 y_4@0 y_3@0 y_2@0 y_1@1 y0@2 y1@2 y2@2 y3@2 y4@2 y5@2 y6@2 y7@2 y8@2;

i s3 sq3 | y_8@0 y_7@0 y_6@0 y_5@0 y_4@0 y_3@0 y_2@0 y_1@0 y0@0 y1@1 y2@2 y3@3 y4@4 y5@5 y6@6 y7@7 y8@8;

!Estimate means
   [i] (ix);
   [s2] (s2x);
   [s3] (s3x);
   [sq3] (sq3x);
```

!Slope equations

Phase 1:	Phase 2:	Phase 3:
py_8 = ix;	py_1 = ix + s2x*1;	py1 = ix + s3x*1 + (1^2)*sq3x;
py_7 = ix;	py0 = ix + s2x*2;	py2 = ix + s3x*2 + (2^2)*sq3x;
py_6 = ix;		py3 = ix + s3x*3 + (3^2)*sq3x;
py_5 = ix;		py4 = ix + s3x*4 + (4^2)*sq3x;
py_4 = ix;		py5 = ix + s3x*5 + (5^2)*sq3x;
py_3 = ix;		py6 = ix + s3x*6 + (6^2)*sq3x;
py_2 = ix;		py7 = ix + s3x*7 + (7^2)*sq3x;
		py8 = ix + s3x*8 + (8^2)*sq3x;

Model 3f (gradual linear + sudden + no change)

!Factor loadings
i s1 | y_8@0 y_7@1 y_6@2 y_5@3 y_4@4 y_3@5 y_2@6 y_1@6 y0@6 y1@6 y2@6 y3@6 y4@6 y5@6 y6@6 y7@6 y8@6;

i s2 | y_8@0 y_7@0 y_6@0 y_5@0 y_4@0 y_3@0 y_2@0 y_1@1 y0@2 y1@2 y2@2 y3@2 y4@2 y5@2 y6@2 y7@2 y8@2;

i s3 | y_8@0 y_7@0 y_6@0 y_5@0 y_4@0 y_3@0 y_2@0 y_1@0 y0@0 y1@1 y2@2 y3@3 y4@4 y5@5 y6@6 y7@7 y8@8;

!Estimate means
[i] (ix);
[s1] (s1x);
[s2] (s2x);
[s3@0];
s3@0;

!Slope equations

Phase 1:	Phase 2:	Phase 3:
py_8 = ix + s1x*0;	py_1 = ix + s2x*1;	py1 = ix;
py_7 = ix + s1x*1;	py0 = ix + s2x*2;	py2 = ix;
py_6 = ix + s1x*2;		py3 = ix;
py_5 = ix + s1x*3;		py4 = ix;
py_4 = ix + s1x*4;		py5 = ix;
py_3 = ix + s1x*5;		py6 = ix;
py_2 = ix + s1x*6;		py7 = ix;
		py8 = ix;

Model 3g (gradual quadratic + sudden + no change)

!Factor loadings
i s1 sq1 | y_8@0 y_7@1 y_6@2 y_5@3 y_4@4 y_3@5 y_2@6 y_1@6 y0@6 y1@6 y2@6 y3@6 y4@6 y5@6 y6@6 y7@6 y8@6;

i s2 | y_8@0 y_7@0 y_6@0 y_5@0 y_4@0 y_3@0 y_2@0 y_1@1 y0@2 y1@2 y2@2 y3@2 y4@2 y5@2 y6@2 y7@2 y8@2;

i s3 | y_8@0 y_7@0 y_6@0 y_5@0 y_4@0 y_3@0 y_2@0 y_1@0 y0@0 y1@1 y2@2 y3@3 y4@4 y5@5 y6@6 y7@7 y8@8;

!Estimate means
[i] (ix);
[s1] (s1x);
[sq1] (sq1x);
[s2] (s2x);
[s3@0];
s3@0;

!Slope equations

Phase 1:	Phase 2:	Phase 3:
py_8 = ix + s1x*0 + (0^2)*sq1x;	py_1 = ix + s2x*1;	py1 = ix;
py_7 = ix + s1x*1 + (1^2)*sq1x;	py0 = ix + s2x*2;	py2 = ix;
py_6 = ix + s1x*2 + (2^2)*sq1x;		py3 = ix;
py_5 = ix + s1x*3 + (3^2)*sq1x;		py4 = ix;
py_4 = ix + s1x*4 + (4^2)*sq1x;		py5 = ix;
py_3 = ix + s1x*5 + (5^2)*sq1x;		py6 = ix;
py_2 = ix + s1x*6 + (6^2)*sq1x;		py7 = ix;
		py8 = ix;

Model 3h (gradual linear 1 + sudden + gradual linear 2)

```
!Factor loadings
i s1 | y_8@0 y_7@1 y_6@2 y_5@3 y_4@4 y_3@5 y_2@6 y_1@6 y0@6 y1@6 y2@6 y3@6 y4@6 y5@6 y6@6 y7@6 y8@6;

i s2 | y_8@0 y_7@0 y_6@0 y_5@0 y_4@0 y_3@0 y_2@0 y_1@1 y0@2 y1@2 y2@2 y3@2 y4@2 y5@2 y6@2 y7@2 y8@2;

i s3 | y_8@0 y_7@0 y_6@0 y_5@0 y_4@0 y_3@0 y_2@0 y_1@0 y0@0 y1@1 y2@2 y3@3 y4@4 y5@5 y6@6 y7@7 y8@8;

!Estimate means
  [i] (ix);
  [s1] (s1x);
  [s2] (s2x);
  [s3] (s3x);

!Slope equations
Phase 1:
py_8 = ix + s1x*0;
py_7 = ix + s1x*1;
py_6 = ix + s1x*2;
py_5 = ix + s1x*3;
py_4 = ix + s1x*4;
py_3 = ix + s1x*5;
py_2 = ix + s1x*6;

Phase 2:
py_1 = ix + s2x*1
py0  = ix + s2x*2;

Phase 3:
py1  = ix + s3x*1;
py2  = ix + s3x*2;
py3  = ix + s3x*3;
py4  = ix + s3x*4;
py5  = ix + s3x*5;
py6  = ix + s3x*6;
py7  = ix + s3x*7;
py8  = ix + s3x*8;
```

Model 3i (gradual linear + sudden + gradual quadratic)

```
!Factor loadings
i s1 | y_8@0 y_7@1 y_6@2 y_5@3 y_4@4 y_3@5 y_2@6 y_1@6 y0@6 y1@6 y2@6 y3@6 y4@6 y5@6 y6@6 y7@6 y8@6;

i s2 | y_8@0 y_7@0 y_6@0 y_5@0 y_4@0 y_3@0 y_2@0 y_1@1 y0@2 y1@2 y2@2 y3@2 y4@2 y5@2 y6@2 y7@2 y8@2;

i s3 sq3 | y_8@0 y_7@0 y_6@0 y_5@0 y_4@0 y_3@0 y_2@0 y_1@0 y0@0 y1@1 y2@2 y3@3 y4@4 y5@5 y6@6 y7@7 y8@8;

!Estimate means
  [i] (ix);
  [s1] (s1x);
  [s2] (s2x);
  [s3] (s3x);
  [sq3] (sq3x);

!Slope equations
Phase 1:
py_8 = ix + s1x*0;
py_7 = ix + s1x*1;
py_6 = ix + s1x*2;
py_5 = ix + s1x*3;
py_4 = ix + s1x*4;
py_3 = ix + s1x*5;
py_2 = ix + s1x*6;

Phase 2:
py_1 = ix + s2x*1;
py0  = ix + s2x*2;

Phase 3:
py1  = ix + s3x*1 + (1^2)*sq3x;
py2  = ix + s3x*2 + (2^2)*sq3x;
py3  = ix + s3x*3 + (3^2)*sq3x;
py4  = ix + s3x*4 + (4^2)*sq3x;
py5  = ix + s3x*5 + (5^2)*sq3x;
py6  = ix + s3x*6 + (6^2)*sq3x;
py7  = ix + s3x*7 + (7^2)*sq3x;
py8  = ix + s3x*8 + (8^2)*sq3x;
```

Model 3j (gradual quadratic + sudden + gradual linear)

```
i s1 sq1 | y_8@0 y_7@1 y_6@2 y_5@3 y_4@4 y_3@5 y_2@6 y_1@6 y0@6 y1@6 y2@6 y3@6 y4@6 y5@6 y6@6 y7@6 y8@6;

i s2 | y_8@0 y_7@0 y_6@0 y_5@0 y_4@0 y_3@0 y_2@0 y_1@1 y0@2 y1@2 y2@2 y3@2 y4@2 y5@2 y6@2 y7@2 y8@2;

i s3 | y_8@0 y_7@0 y_6@0 y_5@0 y_4@0 y_3@0 y_2@0 y_1@0 y0@0 y1@1 y2@2 y3@3 y4@4 y5@5 y6@6 y7@7 y8@8;

  !Estimate means
  [i] (ix);
  [s1] (s1x);
  [sq1] (sq1x);
  [s2] (s2x);
  [s3] (s3x);
```

!Slope equations

Phase 1:	Phase 2:	Phase 3:
py_8 = ix + s1x*0 + (0^2)*sq1x;	py_1 = ix + s2x*1;	py1 = ix + s3x*1;
py_7 = ix + s1x*1 + (1^2)*sq1x;	py0 = ix + s2x*2;	py2 = ix + s3x*2;
py_6 = ix + s1x*2 + (2^2)*sq1x;		py3 = ix + s3x*3;
py_5 = ix + s1x*3 + (3^2)*sq1x;		py4 = ix + s3x*4;
py_4 = ix + s1x*4 + (4^2)*sq1x;		py5 = ix + s3x*5;
py_3 = ix + s1x*5 + (5^2)*sq1x;		py6 = ix + s3x*6;
py_2 = ix + s1x*6 + (6^2)*sq1x;		py7 = ix + s3x*7;
		py8 = ix + s3x*8;

Model 3k (gradual quadratic 1 + sudden + gradual quadratic 2)

```
!Factor loadings
i s1 sq1 | y_8@0 y_7@1 y_6@2 y_5@3 y_4@4 y_3@5 y_2@6 y_1@6 y0@6 y1@6 y2@6 y3@6 y4@6 y5@6 y6@6 y7@6 y8@6;

i s2 | y_8@0 y_7@0 y_6@0 y_5@0 y_4@0 y_3@0 y_2@0 y_1@1 y0@2 y1@2 y2@2 y3@2 y4@2 y5@2 y6@2 y7@2 y8@2;

i s3 sq3 | y_8@0 y_7@0 y_6@0 y_5@0 y_4@0 y_3@0 y_2@0 y_1@0 y0@0 y1@1 y2@2 y3@3 y4@4 y5@5 y6@6 y7@7 y8@8;

!Estimate means
   [i] (ix);
   [s1] (s1x);
   [sq1] (sq1x);
   [s2] (s2x);
   [s3] (s3x);
   [sq3] (sq3x);
```

!Slope equations

Phase 1:	Phase 2:	Phase 3:
py_8 = ix + s1x*0 + (0^2)*sq1x;	py_1 = ix + s2x*1;	py1 = ix + s3x*1 + (1^2)*sq3x;
py_7 = ix + s1x*1 + (1^2)*sq1x;	py0 = ix + s2x*2;	py2 = ix + s3x*2 + (2^2)*sq3x;
py_6 = ix + s1x*2 + (2^2)*sq1x;		py3 = ix + s3x*3 + (3^2)*sq3x;
py_5 = ix + s1x*3 + (3^2)*sq1x;		py4 = ix + s3x*4 + (4^2)*sq3x;
py_4 = ix + s1x*4 + (4^2)*sq1x;		py5 = ix + s3x*5 + (5^2)*sq3x;
py_3 = ix + s1x*5 + (5^2)*sq1x;		py6 = ix + s3x*6 + (6^2)*sq3x;
py_2 = ix + s1x*6 + (6^2)*sq1x;		py7 = ix + s3x*7 + (7^2)*sq3x;
		py8 = ix + s3x*8 + (8^2)*sq3x;

Note. In the slope equations, ‘py’ values represent measurement points centred around relationship dissolution. E.g., ‘py_8’ means eight waves or 22.5 years before the event.

Appendix C

Mplus Specification for the Unconditional Multiple-Group Model (3i)

'ANALYSIS' command input

```
PROCESSORS = 12;
COVERAGE = .001;
TYPE = MIXTURE;
ESTIMATOR = BAYES;
!ALGORITHM = MH;
FBITERATIONS = 300000;
CHAINS = 6;
MODE = ALLFREE;
```

'MODEL' command input

```
%OVERALL%
!Gradual linear
i s1 | y_8@0 y_7@1 y_6@2 y_5@3 y_4@4 y_3@5 y_2@6 y_1@6 y0@6 y1@6 y2@6 y3@6 y4@6 y5@6 y6@6 y7@6 y8@6;

!Sudden
i s2 | y_8@0 y_7@0 y_6@0 y_5@0 y_4@0 y_3@0 y_2@0 y_1@1 y0@2 y1@2 y2@2 y3@2 y4@2 y5@2 y6@2 y7@2 y8@2;

!Gradual quadratic
i s3 sq3 | y_8@0 y_7@0 y_6@0 y_5@0 y_4@0 y_3@0 y_2@0 y_1@0 y0@0 y1@1 y2@2 y3@3 y4@4 y5@5 y6@6 y7@7 y8@8;

!Estimate means
[i] (ix);
[s1] (s1x);
[s2] (s2x);
[s3] (s3x);
[sq3] (sq3x);

!Variability
i (vi);
s1 (vs1);
s2 (vs2);
s3 (vs3);
sq3 (vsq3);

%c#1% !Controls

i (a1);
s1 (a2);
s2 (a3);
s3 (a4);
i WITH s1 (a5);
i WITH s2 (a6);
i WITH s3 (a7);
i WITH sq3 (a8);

[i] (iax);
[s1] (s1ax);
[s2] (s2ax);
[s3] (s3ax);
[sq3] (sq3ax);

i (via);
s1 (vs1a);
s2 (vs2a);
s3 (vs3a);
sq3 (vsq3a);

%c#2% !Divorced

i (b1);
s1 (b2);
s2 (b3);
s3 (b4);
i WITH s1 (b5);
i WITH s2 (b6);
i WITH s3 (b7);
i WITH sq3 (b8);

[i] (ibx);
[s1] (s1bx);
[s2] (s2bx);
[s3] (s3bx);
[sq3] (sq3bx);

i (vib);
s1 (vs1b);
s2 (vs2b);
s3 (vs3b);
sq3 (vsq3b);
```

'MODEL CONSTRAINT' command input

```
New (diff_vi  diff_vs1  diff_vs2  diff_vs3  diff_vsq
     gdif_i  gdif_s1 gdif_s2  gdif_s3 gdif_sq3);

!Differences in intercept and slopes across groups
gdif_i = ibx - iax;
gdif_s1 = s1bx - s1ax;
gdif_s2 = s2bx - s2ax;
gdif_s3 = s3bx - s3ax;
gdif_sq3 = sq3bx - sq3ax;

!Differences in variance across groups
diff_vi = vib - via;
diff_vs1 = vs1b - vs1a;
diff_vs2 = vs2b - vs2a;
diff_vs3 = vs3b - vs3a;
diff_vsq = vsq3b - vsq3a;
```

'MODEL TEST' command input	
!Group differences on means	!Group differences on variance
gdif_i = 0;	diff_vi = 0;
gdif_s1 = 0;	diff_vs1 = 0;
gdif_s2 = 0;	diff_vs2 = 0;
gdif_s3 = 0;	diff_vs3 = 0;
gdif_sq3 = 0;	diff_vsq = 0;

Note. We ran this multiple-group model 10 times, each time with a different equation in the 'MODEL TEST' command, as Mplus only conducts Wald tests on one parameter at a time**.** The commands used in each run are shown in the last row of the table (e.g., gdif_i = 0 in the first run, gdif_s1 = 0 in the second run, etc.).

Appendix D

Descriptive Statistics for Moderator Variables Used in Conditional Models

	Exposure group (*n* = 1,462)	Control Group (*n* = 2,666)
Moderator variable	*n* (%)	*n* (%)
Education (at Wave 1)		
High school only	940 (64.6)	1,705 (64.8)
Further study	510 (35.4)	933 (35.2)
Re-partnering		
Yes	483 (33.0)	
No	979 (67.0)	
Moderator variable	*M* (*SD*)	*M* (*SD*)
Subjective income		
Linear Δ1 average	3.03 (0.91)	3.17 (0.87)
Linear Δ2 average	3.29 (0.91)	3.61 (0.86)
Linear Δ3 average	3.43 (0.80)	3.76 (0.73)
Social support		
Linear Δ1 average	3.66 (0.96)	3.94 (0.87)
Linear Δ2 average	3.43 (0.99)	3.95 (0.88)
Linear Δ3 average	3.49 (0.94)	4.06 (0.78)
Perceived control		
Linear Δ1 average	3.03 (0.81)	3.25 (0.75)
Linear Δ2 average	3.07 (0.79)	3.26 (0.78)
Linear Δ3 average	3.24 (0.74)	3.31 (0.72)

Note. ‘Linear Δ’ represents the phase of relationship dissolution, i.e., ‘Linear Δ1 average’ refers to the average value of a moderator variable during the pre-dissolution phase. The perceived control values displayed are the averages divided by 6. Descriptive statistics for having children (moderator) remain unchanged from propensity-score matching and are displayed in Table 2 in the Results section.

Appendix E

Estimated Life Satisfaction Scores Across the 17 Measurement Points for the Exposure and Control Group (Model 3i)

Measurement point (years, centred on relationship dissolution)	Exposure group	Control group
−22.5	2.993	3.025
−19.5	2.992	3.032
−16.5	2.990	3.038
−13.5	2.989	3.044
−10.5	2.988	3.050
−7.5	2.986	3.057
−4.5	2.985	3.063
−1.5	2.928	3.033
1.5	2.862	3.040
4.5	3.056	3.059
7.5	3.112	3.092
10.5	3.163	3.124
13.5	3.208	3.154
16.5	3.247	3.183
19.5	3.280	3.211
22.5	3.307	3.237
25.5	3.328	3.262