Social Support and Life Satisfaction among Entrepreneurs: A Latent Growth Curve Modelling Approach

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Abstract

Purpose: Social support has been identified as a valuable resource that could help entrepreneurs maintain goal directness in their endeavours and increase their life satisfaction. However, to date scant research has examined the effect of perceived social support on life satisfaction during the transition from paid employment to self-employment. This paper uses the Job Demand Resource Model (JD-R) as a theoretical lens to investigate this relationship.

Methodology: Drawing on the Household Income and Labour Dynamics in Australia (HILDA)\(^1\) survey, we use latent growth curve modelling (LGCM) to investigate the trajectories of entrepreneurs’ perceived social support and life satisfaction (n=1,303) up to five years after their transition into self-employment.

Findings: Results suggest that entrepreneurs experience a boost in life satisfaction in the transition phase, followed by a declining trend in the years that follow. We find that both the initial perception and the evolution of perceived social support are positively related to life satisfaction over time across gender groups. However, we find that females may benefit more from early social support soon after the transition into self-employment to forestall declines in life satisfaction over the long-term.

Originality/value: This study extends the JD-R literature by examining the transition into self-employment, considered an “active job” characterised by high demands and high decision latitude. LGCM modelling captures how both initial levels and changes in social support affect life satisfaction during entrepreneurship entry and over time.

Research limitations/implications: The generalisability of the research findings beyond the Australian context is undefined. Future research needs to examine to what extent these results can generalise to other samples within different cultural and institutional frameworks.

Practical implications: Since perceived social support is a strong buffering mechanism that helps mitigate job demands, entrepreneurs need to be proactive in building a strong network. Individuals who switch to self-employment should carefully map and build a strong social network that can help them weather the challenges and setbacks in their new job.

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\(^1\) This paper uses unit record data from the Household, Income and Labour Dynamics in Australia (HILDA) Survey. The HILDA Project was initiated and is funded by the Australian Government Department of Social Services (DSS) and is managed by the Melbourne Institute of Applied Economic and Social Research (Melbourne Institute).
1. **Introduction**

A considerable amount of research effort has been expended on improving our understanding of entrepreneurs’ life satisfaction in recent times (Binder, 2018; Dijkhuizen *et al.*, 2017; Georgellis and Yusuf, 2016; van der Zwan *et al.*, 2018). These studies have shown that entrepreneurs are in general more satisfied with their lives than paid workers are. Scholars attribute this markedly higher satisfaction to the job of the entrepreneur being characterised by autonomy, flexibility, skill utilisation and a greater variety of tasks (Benz and Frey, 2008; Blanchflower, 2000).

Recent research has focused on within-individual variation of the returns to entrepreneurship, investigating individual entrepreneurs as they transition into self-employment (Chadi and Hetschko, 2017; van der Zwan *et al.*, 2018). This stream of literature suggests that entrepreneurs enjoy only a temporary boost in job satisfaction during the transition phase. Over time, they go back to the base line ‘adaptation process’ once the ‘honeymoon-hangover effect’ dissipates (Georgellis and Yusuf, 2016; Hanglberger and Merz, 2015). The same pattern of trajectory applies to life satisfaction (Binder and Coad, 2013, 2016; van der Zwan *et al.*, 2018).

Quitting paid employment to start a new venture can be a very lonely experience (Stephan, 2018). In addition, entrepreneurship is like a rollercoaster journey where breakthroughs are interspersed with numerous failures, setbacks and near misses (Clarke and Holt, 2016). In this context, social support has been identified as a key resource to help entrepreneurs cope with stressful situations (Boz Semerci and Volery, 2018; Davidson *et al.*, 2010). This concept captures the individual’s perception that he or she is cared for, valued, and has people on whom they can relate to at the time (Zhu *et al.*, 2017). Social support helps entrepreneurs to share a wide range of issues with others, to obtain empathy and to try out new perspectives and ideas (Boz Semerci and Volery, 2018).

Drawing on the Job Demands-Resources (JD-R) model (Bakker and Demerouti 2007; Demerouti and Bakker, 2011), the objective of this study is to investigate the role of perceived social support (PSS) on life satisfaction during entrepreneurship entry. Specifically, we posit that PSS is an important resource and we examine whether the initial level of PSS and its evolution over time affects entrepreneur life satisfaction during the transition into self-employment and beyond. Furthermore, recognising the influence of gender on vocational behaviour (Ahl, 2006; Marlow, 1997) and support-relevant social interactions (Eagly, 1997;
Matud et al., 2003), we examine gender differences around the nexus of entry into self-employment, PSS, and life satisfaction.

Entrepreneur well-being is an area of research still in its infancy, with studies mainly from the economics and labour economic disciplines (Georgellis and Yusuf, 2016; van der Zwan et al., 2018). The recent years have seen a shift in focus away from comparing well-being across individuals to comparing within individuals over time, motivated by increased availability of longitudinal data and the need to gain insight into the rate of change and how initial PSS levels affect an entrepreneur’s subjective well-being over time. In this study, we adopt the hedonic approach to subjective well-being (Stephan, 2018), namely life satisfaction, and we use both terms interchangeably. This approach characterises well-being through the attainment of pleasure, avoidance of pain, and satisfaction with various domains of life.

The contribution of the study is threefold. Firstly, at a theoretical level, this study extends the JD-R literature by examining the transition into self-employment, considered an ‘active job’ characterised by high demands and high autonomy. In this context, our results suggest that job decision latitude only partly buffers against the negative effects of high demands on entrepreneur life satisfaction and that social support is a key resource to maintain satisfaction. Secondly, from a methodological perspective, we adopt a sophisticated modelling approach, namely Latent Growth Curve Modelling (LGCM), to explore the trajectory of life satisfaction among entrepreneurs. Our study assesses within-individual variation of the returns from entrepreneurship, which effectively eliminates unobservable pooling effects (Åstebro and Chen, 2014). In addition, the method allows us to simultaneously investigate how initial levels and changes in social support relate to life satisfaction. Thirdly, our approach provides a longitudinal perspective on entrepreneur well-being. This is critical since entrepreneurship is a long-term process which requires an understanding of the evolution of the rewards before and after entrepreneurship entry (Clarke and Holt, 2016). We draw on 16 waves from the Household, Income and Labour Dynamics in Australia (HILDA) survey and follow within this period individual PSS and life satisfaction trajectories for up to five years after a transition into self-employment.
2. Theoretical anchor and hypothesis development

2.1. Job Demands-Resources and life satisfaction of entrepreneurs

The Job Demands-Resources (JD-R) model (Bakker and Demerouti, 2007; Demerouti and Bakker, 2011) provides a theoretical lens for conceptualising the characteristics of self-employment and their implications for life satisfaction. Broadly conceived, it proposes that well-being across occupations, after controlling for personality, stems from two general job related sources: job demands and job resources (Bakker et al., 2010). Job demands refer to the physical, psychological, social and organisational aspects of a job that require sustained physical, mental and emotional effort and are therefore associated with physiological costs such as stress or exhaustion (Bakker et al., 2007; Nahrgang et al., 2011). Examples of job demands include conflicting demands, job ambiguity, workload, and time pressure. Conversely, job resources refer to physical, psychological, social and organisational aspects of the job that help achieve work goals, reduce job demands and the associated physiological or psychological costs, or, stimulate learning and personal development (Bakker et al., 2007; Schaufeli and Bakker, 2004). Examples of job resources include autonomy, social support and performance feedback.

JD-R theory draws on the well-established Job Demand-Control (JDC) model (Karasek, 1979), which states that two occupational characteristics of the work environment, job demand and job control, interact to influence worker well-being and health. In addition to the aforementioned job demands, JDC considers job control, the decision latitude over job performance that relates to factors such as how and when a job task is completed. The basic prediction of the JDC model is the ‘strain hypothesis’: job demand increases work-related stress, whereas job control decreases it in an additive fashion. The second prediction, in line with the first prediction, is the ‘buffer hypothesis’, which entails a multiplicative effect of job demand and job control on well-being (van der Doef and Maes, 1999), in such a way that control can moderate the negative effects of high demands on well-being. In other words, job control enhances one's feelings of being able to cope with job demands (Karasek, 1979). JDC suggests that the most detrimental consequences on well-being arise when the psychological demands of the job are high and the decision latitude of the worker is low (Theorell and Karasek, 1996).

JD-R expands the JDC model by reasoning that different job resources, not just control, can act as buffers for a variety of different job demands (Bakker et al., 2005). The central
assumption in the JD-R Model is that work-related strain develops when certain job demands are high but job resources are limited, undermining well-being and work engagement (Bakker et al., 2007). In contrast, when job resources are high, the motivational process is activated, leading to work engagement and higher work performance (Schaufeli and Bakker, 2004; Bakker et al., 2005).

Self-employment typically combines high decision control and high job demand, a situation characterised as an ‘active job’. Running your own business entails autonomy, flexibility, task identity and task variety, all of which can potentially induce higher job satisfaction (Benz and Frey, 2008; Blanchflower, 2000). In addition, entrepreneurship enhances subjective well-being by meeting vital psychological needs. It has been suggested that freedom and autonomy provide a ‘procedural utility’, as entrepreneurs value not so much the outcomes, but the conditions and processes leading to these outcomes (Benz and Frey, 2004). Thus, entrepreneurs derive happiness from being able to do what they like (Nikolova, 2018).

Nonetheless, self-employment is a high-demand job. Entrepreneurs tend to work longer and more irregular hours than employees (Åstebro and Chen, 2014; Levine and Rubinstein, 2012); and their work is characterised by high pace, brevity and fragmentation. Entrepreneurs running a business with employees must also cope with multiple demands and diverging expectations (Cowling et al., 2004). Self-employment could worsen life satisfaction if it entails loneliness, reduced socialisation, immersion in business, and the pressure to achieve (Cardon and Patel, 2015; Jamal, 1997). However, in ‘active jobs’ the combination of high job control with high job demand leads to ‘desirable stress’ (Karasek, 1979; Theorell and Karasek, 1996), as individuals are likely to learn new things and develop new skills. Therefore, self-employment can be considered as motivating and stimulating, and this reduces the downward impacts on life satisfaction.

Although the literature provides considerable support for the strain hypothesis, support for the buffer hypothesis – stating that control can moderate the negative effects of high demands on well-being – is less consistent (Binder and Coad, 2016; van der Zwan et al., 2018; van der Doef and Maes, 1999). This suggests that job control only partly buffers against the impact of job demands on entrepreneur well-being.

As nascent entrepreneurs pass the initial euphoric launch stage and struggle to establish their business, many of them realise the gruelling reality of self-employment and that their venture may end up failing. This scenario is particularly plausible because of the overt optimism
characterising most self-employed individuals (Cassar, 2010). In this vein, The Economist (2014, p. 66) remarked: “It is fashionable to romanticize entrepreneurs. But the reality can be as romantic as chewing glass: first-time founders have the job security of zero-hour contract workers, the money worries of chronic gamblers and the social life of hermits.” As the harsh reality of running their own business becomes apparent, entrepreneurs are likely to experience a decline in life satisfaction, bringing it back to the baseline (Georgellis and Yusuf, 2016).

Recent empirical studies suggest that while individuals experience a boost in satisfaction when entering self-employment, this feeling declines in the years following the transition to self-employment (Hanglberger and Merz, 2015; van der Zwan et al., 2018). The organizational psychology literature called this short-lived spike “the honeymoon effect” (Boswell et al., 2005), capturing the effect of a new job in general. Using the German Socio-Economic Panel Study, Chadi and Hetschko (2017) identified a similar ‘anticipation and adaption effect’ when studying job satisfaction. In the same vein, van der Zwan et al. (2018) found few rewards in terms of life satisfaction, and that higher work satisfaction may come at the cost of decreased individual satisfaction in the important life domain of leisure. Thus, we hypothesize that

H1: When switching from paid to self-employment, entrepreneurs will experience an immediate boost in their life satisfaction and then a decline over time.

2.2. Perceived social support

JD-R research indicates that effective buffering takes place when job demands and resources (and not only control) interact to predict engagement, which enhances well-being. A high level of control over the work situation, manageable work demands and pertinent resources are crucial factors an employee needs to be able to experience for a high level of job and life satisfaction (de Lange et al., 2003; van Woerkom et al., 2016). We posit that social support is a key resource for entrepreneurs attempting to cope with stressful situations, especially during the transition into self-employment, when they leave their familiar work environment and co-workers to start a venture on their own.

PSS refers to an individual’s perception of the support acquired from their environment. It is a complex construct that encompasses a sense of connection and relatedness (Barrera, 1986). PSS can either be emotional, material, or informational (Keat et al., 2011). It is an individual’s perception of receiving support which is critical; in fact, research indicates that perceived
support contributes just as much to health and well-being outcomes compared to the existence of actual support (i.e. received social support) (Lakey, 2013).

In addition, the entrepreneur’s direct or tacit support from social ties contributes significantly to his or her success in business (McDowell et al., 2019). For instance, social support increases the chance of business survival and helps the entrepreneur in manoeuvring various business hurdles that come in the form of financial constraints or legal troubles (Kar, 2017). Similarly, social support provided by family members reduces the exit likelihood from entrepreneurship (Revilla et al., 2016; Zhu et al., 2017). Without adequate social support systems, entrepreneurs find it harder to succeed as they will have to rely on their (limited) own knowledge and expertise (Bird and Wennberg, 2016).

We recognise the potential bidirectionality between social support and life satisfaction. Individuals who receive social support are likely to experience greater life satisfaction, but the level of life satisfaction may also cause changes in perceptions of social support. Because the impetus behind this research is to identify the buffering mechanism of PSS during entrepreneurship entry (rather than the longitudinal causality between PSS and well-being), we posit that social support drives well-being outcomes. Specifically, we propose that people will enter self-employment with different levels of PSS, and that those who initially report higher levels will have a higher life satisfaction. A high level of PSS will slow down the decline in life satisfaction, once entrepreneurs pass the “honeymoon phase” in the years following the transition to self-employment. Thus,

H2a: The initial level of social support will positively influence the initial level of life satisfaction.

H2b: Social support will slow down the declining slope of life satisfaction in the years following the transition into self-employment.

2.3. Gender perspective

A vast stream of the literature in entrepreneurship suggests that female entrepreneurs and the characteristics of their ventures are significantly different from that of men (Ahl, 2006). Among other things, female founders report being more satisfied with their business in comparison to male entrepreneurs (Carree and Verheul, 2012; Crum and Chen, 2015).

However, the transition into self-employment poses a number of challenges for female entrepreneurs. Traditional gender norms appear to be strongly reflected amongst the self-
employed (Ahl, 2006). Eib and Siegert (2019, p. 1) recently remarked in this respect that, “Many women-operated firms reflect feminized working patterns, such as working part-time or basing the business within the home, which, as a result, reinforces the perception of women as mothers and care-takers first”. This view follows social role theory (Eagly, 1997), suggesting that men are more likely to fulfil roles outside the home and be the main breadwinner, whereas women are generally responsible for childrearing and other domestic tasks. Because of the demands associated with their dual role of child-rearing and entrepreneurship, women tend to experience a higher prevalence of work-family conflicts and parenting stress (Cabrera and Mauricio, 2017; Marlow, 1997).

In addition, women are more likely to experience financial and social stressors during a business launch. Chadwick and Raver (2019), found that female entrepreneurs tend to feel more stressed when they face high financial need and when they perceive low social support in their environment. These higher stress appraisals among women persist several months later during business operation compared with their male counterparts (Chadwick and Raver, 2019). Against this backdrop, social support is a key resource to help coping with stressful situations (Boz et al., 2018). However, a gender-stratified analysis reveals a different pattern between males and females in respect to social support and its impact on life satisfaction. Firstly, empirical studies suggest that women have more extensive, better and varied social relations than men (Fuhrer and Stansfeld, 2002). They provide and receive more support and have a wider “net of concern” than men; that is to say, they spend more time involved in responding to requests and support from other people (Johansson et al., 2016). Furthermore, women have a greater propensity to seek social support especially during stressful events and they can more readily mobilise support when in need (Liebler and Sandefur, 2002). Women also have larger social networks outside of work (Johansson et al., 2016).

Secondly, women tend to perceive, seek, and use social support differently. For example, when examining the differences between genders with respect to the effect of perceived job demands, control, and support, Rivera-Torres et al. (2013) found that social support has a stronger weakening effect on the levels of job stress for women than men. Thus, we formulate the following hypothesis:

**H3a**: Female entrepreneurs will gain a larger increase in life satisfaction from perceived social support than men when entering self-employment.
H3b: Over time, the effect of perceived social support on life satisfaction will be stronger for female entrepreneurs than for male entrepreneurs.

3. Data and method

This study draws on 16 waves of Household, Income and Labour Dynamics in Australia (HILDA) survey data. This nationally representative household-based panel study began in 2001 and covers around 9,835 households. Entrepreneurs were identified based on their occupational status, and we use the terms ‘entrepreneurs’ and ‘self-employed’ interchangeably. Our definition of self-employment follows Wooden and Watson (2007), in that it includes all types of entrepreneurs regardless if they had incorporated their business or not. In other words, both owner-managers who operate their own incorporated businesses and people who operate their own unincorporated business were included in the study.

Further, we define entrepreneurship transition as the change in the occupational status from one year to the next, i.e. change from paid employment in year (t) to being self-employed in year (t+1). This identification approach is customary in economics and entrepreneurship research (Nikolova, 2018; van der Zwan et al., 2018). A total of 2,711 individuals who made the transition from paid employment to self-employment at some stage (unbalanced panel) were identified. In a second stage, 467 observations involving multiple spells of self-employment were excluded; this focus helps us filter out “job hoppers” (Failla et al., 2017).

The baseline for the analysis was set to one year before the transition to self-employment and five years after the transition; This baseline provides an optimal initial status measure to consider the impact of PSS in shaping the trajectories of life satisfaction. Those who change their status between waves to any other labour status but self-employment were excluded automatically. Of the original sample, 39% remained self-employed in the fifth year. To capture the (linear or non-linear) trajectory after the transition into self-employment and the parallel processes of PSS and life satisfaction, any individual with less than four waves of measurement was excluded. This procedure was intended to identify true change from measurement errors (Preacher et al., 2008). Following these different steps, the final sample included 1,303 individuals. Missing data arising from this sampling strategy are discussed in the results section.
3.1. Measurement

Life satisfaction was measured using self-reported level of satisfaction with life on a scale from 0 (completely dissatisfied) to 10 (completely satisfied). The exact question was “All things considered, how satisfied are you with your life?” and it was included in all waves of HILDA. This single item was adopted in several past studies (Benz and Frey 2008; Blanchflower, 2000), and it is considered very similar to more psychometrically established multiple-item scales (Andersson, 2008; Binder and Coad, 2016; Binder, 2018). Following Hahn's et al. (2015) approach, we mean-centred the life satisfaction score within each wave in relation to the average value for the total HILDA sample. This procedure allows controlling for any other major life events and facilitates the interpretation of the coefficients. Further, the trend of the centered scores followed the same trend as the raw data averages over time, implying the absence of any systematic changes that could have been hidden by the centering procedure.

PSS was measured with 10 items (Table 1) capturing the entrepreneur’s beliefs and expectations about the assistance and advice that he/she may receive from his/her social groups. The construct was measured using a seven-point Likert scale (1 = strongly disagree to 7 = strongly agree). The first seven items were adopted from Henderson et al. (1978), while the last three items were from Marshall and Barnett (1993). Confirmatory factor analysis was applied and confirmed the factorial invariant across measurement waves with acceptable fit (CFI = 0.93, TLI = 0.92, RMSEA = 0.034) and a significant $\chi^2$ difference test compared to the fully constrained model ($\Delta\chi^2 (78) = 214.663, p < 0.001$). The factor scores were calculated by weighting items based on the factor loadings from the CFA, with a higher score indicating that a person perceives to have a strong social support.

3.2. Statistical analysis

The Latent Growth Curve modelling (LGCM) technique was used to examine the intra-individual change and inter-individual change over time (Preacher et al., 2008). LGCM helps to circumvent limitations of past studies on life satisfaction, which relied on fixed effect regression analysis. These studies have been unable to examine social support and life satisfaction together in a single model except by splitting the sample into low and high social support categories. Recent studies (e.g. Milner et al., 2016) typically used fixed effect regression to examine the effect of perceived social support on mental health for employed and
unemployed individuals. However, these studies were not able to explain the dynamic of the developmental processes of social support and mental health over time using regression.

LGCM offers several advantages. Firstly, it allows researchers to simultaneously investigate how initial levels and changes in PSS are linked to life satisfaction. Secondly, LGCM techniques estimate the average rate of change of the sample over time, as well as the variability of that change within the sample. This facilitates understanding of both the average change in life satisfaction among entrepreneurs and also the individual variation, shedding some light about the role PSS plays and why some entrepreneurs experience changes and others do not (i.e. the individual differences in initial status and in the growth over time). Thirdly, LGCM has the capability to explicitly assess and model measurement error variance at particular time points (Preacher et al., 2008). Finally, LGCM can reduce the bias introduced by attrition rate which is expected in longitudinal studies (Curran et al., 2010).

In implementing LGCM, we followed a two-step procedure (Preacher et al., 2008). The conceptual model is shown in Figure 1. In the first step, we measured the changes in PSS and life satisfaction over the course of five years after the transition into self-employment. Unconditional LGCM models were computed separately for PSS and life satisfaction. In LGCM, the intercept describes the initial values of the variable, and since it is constant for each subject over time, it has a factor loading of 1. The slope describes change over time, which can take a linear or non-linear developmental form. Several forms of growth were tested: (1) a free LGCM with unspecified growth function which allowed us to freely estimate the slope means and determine the best fit based on the data (i.e., the parameterization of time in the factor loading matrix were freely estimated after the transition -1, *, *, *, *, *, and 1); (2) a linear LGCM that tested the assumption of a linear increase or decrease in the construct (i.e., fixing the loadings of the slope to 0, 1, 2, 3, 4, 5, 6); and (3) a quadratic LGCM by adding a quadratic slope (i.e., fixing the loadings to 0, 1, 4, 9, 16, 25, 36) testing the assumption that the construct followed a curvilinear pattern.

In the next step, in order to investigate the extent to which entrepreneur PSS predicts the level of and the changes in life satisfaction, a parallel process model was computed. This captured the developmental process of the two latent variables simultaneously. Finally, a parallel process model was testing differences between females and males.

- Insert Figure 1 here -
The following fit indexes are reported: $\chi^2$, Root Mean Squared Error of Approximation (RMSEA), Akaike's Information Criterion (AIC), Bentler Comparative Fit Index (CFI), and Tucker Lewis Index (TLI). For RMSEA, a value less than .05 will be taken as evidence of a good fit. For AIC, the lower the value the better fit. Both CFI, and TLI values greater than 0.95 indicate excellent fit. All analyses were conducted using the maximum likelihood estimation, a suitable approach to handling missing observations in AMOS 25 (Arbuckle, 2014).

4. Results

4.1. Sample Characteristics and preliminary analysis

Table 2 reveals that the average age of participants in the year before the transition was 39, and the majority (64.9%) were male. The level of educational attainment was as follows: 13.6% postgraduate degree, 26.6% undergraduate degree, and the majority (59.8%) had a vocational degree or had completed high school. The average income in the baseline year was around A$10,430. The majority of people (55.5%) in our sample were married and the minority (15%) were suffering from a long-term health condition, and 35.1% of people in the sample did not have children.

As stated previously, since LGCM uses maximum likelihood estimation, it does not require complete data to estimate an average intercept and rate of change. Therefore, missing data do not affect the parameter estimate (Curran et al., 2010). However, a minimum of four observations was deemed necessary to establish the trajectory. Missing data analysis was conducted to identify any substantial baseline differences between the included (n = 1,303) and excluded data (n = 870) (Table 3). Compared with entrepreneurs in the analytic sample, those who had less than four waves of data were younger, mostly female, with lower income, and lower educational attainment. However, all the aforementioned differences are marginal, with a small effect size.

- Insert Table 2 here –
- Insert Table 3 here –
4.2. **General trends**

Figure 2 and 3 illustrate the general trend in PSS and life satisfaction based on the raw average score. PSS decreased in the first two years after the transition and levelled up after the third year. Furthermore, PSS remained almost constant for both genders. However, women reported higher levels of PSS compared to men. The trend for life satisfaction indicates that the means generally increased over the first period of the transition. The biggest positive change occurred in the first year after transition and increased at a slower rate thereafter. In terms of the average life satisfaction, there is a different pattern of change by gender. Figures 2 and 3 suggest that there is sufficient variability in PSS and life satisfaction scores for testing the parallel process model.

- Insert Figure 2 here –

- Insert Figure 3 here –

4.3. **Unconditional LGCM social support**

The Likelihood ratio tests for nested models (Table 4) were applied to determine which model provided the best fit to the data. The linear model was adapted for its parsimony and consistency with other models used in developmental studies (Pettit et al., 2011). The linear LGCM for social support matched the data well ($\chi^2 = 36.245$, df = 23, RMSEA = 0.021, TLI=0.995, CFI = 0.996, AIC=60.245). The intercept’s mean was around 0.005 and the slope’s mean indicated a non-significant general change over time (-0.034; p = 0.320). Furthermore, the initial start and rate of change were heterogeneous among the group given the significant variance around the mean slope (0.005; p < 0.001) and the mean intercept (0.604; p < 0.001).

The estimated covariance between the slope and intercept was not significant (-0.007; p = 0.122), suggesting that the rate of decline in perceived social support over time was similar for individuals who initially started with either high or low scores.

Running a multi group LGCM by gender reveals interesting results. Females have a slightly upward trajectory as indicted by the mean intercept (-0.002; p = 0.831) and mean slope (0.175; p < 0.001). In contrast, males have a declining trajectory suggested by the mean intercept (0.009, p = 0.160) and mean slope (-0.150; p < 0.001). The analysis of variance in the trajectory of both males and females showed a significant variation in the initial start (0.594, p < 0.001 for males, 0.554, p < 0.001 for females) and rate of change (0.006, p < 0.001 for males, 0.003, p < 0.001 for females).
4.4. Unconditional LGCM life satisfaction

Among the several forms of growth tested (Table 4), the free LGCM was selected, where the optimal growth trajectories can be determined from the observed data ($\chi^2 = 35.579$, df = 19, RMSEA = 0.031, TLI = 0.993, CFI = 0.996, AIC = 64.269). The free LGCM best captures the complexity of the observed trajectories within the data; it describes the boost and downturn over time beyond what is predicted by the nonlinear factor (Figure 4 illustrates the estimates of single average growth and a single variance of the LGCM parameters, which are distinct from the observed means displayed in Figure 3). The slope loading estimates were also used in the parallel process model. The predicted trajectory of life satisfaction shows a significant decline especially between year 0 and year 5, suggesting a “honeymoon-hangover” effect, which confirms H1. There was a significant difference in the initial level of life satisfaction in the sample around a mean intercept (-0.081, p = 0.006) and mean slope (-0.021; p < 0.001). In addition, we found a significant variance of the intercept (0.998; p < 0.001) and the slope (0.162; p < 0.001) confirming the variability of life satisfaction trajectories.

The multigroup analysis revealed a difference between the female and male trajectories. The parameter estimates showed a mean intercept of -0.145 (p < 0.001) and a mean slope of -0.035 (p < 0.001), indicating a slight downward trajectory for males. The mean intercept of 0.020 (p < 0.001) and a mean slope of -0.020 (p < 0.001) indicated a modest downward trajectory for females. The analysis of variance in the trajectory of life satisfaction showed that the variability in the initial status and the growth rate of life satisfaction were significant for both males and females, indicating the presence of gender differences in the growth of life satisfaction.

- Insert Table 4 here –
- Insert Figure 4 here –

4.5. Parallel Process Model

The parallel process model showed a good fit with data as detailed in Table 5. In Model-A, we estimated the effect of the intercept and slope of PSS on the intercept and slope of life satisfaction. In both cases, there was a statistically significant positive effect. This indicates that the initial level of PSS is related to the initial level of life satisfaction ($\beta = 0.555; p < 0.001$)
and that the change of PSS is related to the change of life satisfaction ($\beta = 0.680; p < 0.001$), thus supporting H2a and H2b.

In Model-B (Table 5), we estimated the effect of the initial status of PSS on the change of life satisfaction. The results indicate that any increase in the level of PSS in the initial phase will slow the decline of life satisfaction ($\beta = -0.056; p < 0.001$). Comparing the two nested models using the likelihood ratio $\chi^2$ difference test ($\Delta \chi^2 = 34.551; \Delta df = 1; p < 0.001$); suggests that adding the extra parameter (i.e. the path from the intercept of social support to the slope of life satisfaction) is significant. These results further support H2b.

When comparing between male and female entrepreneurs, the significant relationship between the intercept and slope of both processes remained, lending support to H3a (Table 6). However, the effect of the initial level of perceived social support on the change rate of life satisfaction (Model-B, Table 6) was significant only for female entrepreneurs ($\beta = -0.155; p < 0.001$) and not for males ($\beta = -0.028; p > 0.050$). The gender moderation test reveals that females and males differ significantly with respect to the impact of the initial level of social support on life satisfaction ($\Delta \chi^2 = 13.712; \Delta df = 8; p = 0.022$); partially supporting H3b. This means that the female entrepreneurs value social support more than male counterparts, and as they feel socially connected, they enjoy higher life satisfaction and experience a smaller decline over time.

5. Discussion and Conclusion

In this study we examine the role of PSS on entrepreneur life satisfaction during the transition into self-employment and beyond. Drawing on the Job Demands-Resources (JD-R) model, we argued that PSS is a key resource for entrepreneurs to cope with stressful situations, especially during the transition into self-employment. We adopted a sophisticated and rigorous approach, LGCM, to show that PSS is associated with changes in life satisfaction and to uncover how gender affects this co-development process over time.

Our findings provide evidence of a boost in life satisfaction in the transition phase, followed by a declining trend in the years that follow. This is in line with recent research on life satisfaction and entrepreneurship entry (Georgellis and Yusuf, 2016; Hanglberger and Merz,
Our results suggest that the “honeymoon-hangover effect” or “adaption process” (Boswell et al., 2005; 2009), does not just affect employees changing jobs but is applicable to nascent entrepreneurs as well. These findings also challenge the traditional assumption that entrepreneurs are generally highly satisfied (Benz and Frey, 2008; Schneck, 2014). Indeed, our analysis provides a contrasting picture, showing that the increase in life satisfaction is temporary, and that becoming an entrepreneur is often not the rosy, life-improving experience often portrayed by scholars and the public media alike.

In addition, our findings extend the JD-R and JDC theory by examining the transition into self-employment, a typically “active job”. Specifically, it appears that job decision latitude only partially buffers against the negative effects of high demands of the entrepreneur’s job. This lends support to the recent literature, which has cast doubts about the predictive value of the buffer hypothesis (Binder and Coad, 2016; van der Zwan et al., 2018).

The analysis confirmed our prediction that the longitudinal effects of PSS on entrepreneur life satisfaction are statistically significant, and that both the initial perception and evolution of PSS are positively related to life satisfaction over time. In line with JD-R, our results suggest that PSS can serve as a strong personal buffer, especially in stressful times (Boz Semerci and Volery, 2018). Entrepreneurs who reported a higher initial level of social support experienced less decline in life satisfaction after their transition into self-employment, perhaps because the emotional, informational, and physical resources drawn from their social network helped them to persist after launching their business. In other words, PSS helps mitigate the “hangover effect” that follows job change (Boswell et al., 2005). In particular, social support can help entrepreneurs manoeuvre the numerous hurdles (e.g., resource constraints, legal challenges, lack of reputation) in the early stages of their start-up. Our findings therefore contribute to the JD-R model, showing that PSS translates into higher levels of life satisfaction, which can potentially prevent job disengagement (Bakker and Demerouti 2007; Demerouti and Bakker, 2011). This is all the more important given that entrepreneurs often have a very low propensity for help-seeking behaviour (Williams et al., 2019).

Individuals who switch to self-employment should therefore carefully map and build a strong social network that can help them weather the challenges and setbacks in their new job. The results indicate that the perception of a strong social network reducing job demands that are associated with starting a new venture is pertinent. This means that social support may enhance nascent entrepreneur ability to cope with “occupational loneliness”, a perennial issue in self-employment (Fernet et al., 2016). Identifying social support is the first step in building a more
comprehensive resource kit that helps entrepreneurs to handle their job demands and achieve their personal objectives.

Our multigroup analysis indicated that gender matters. This suggests that perceived social support is more important for females than for males and that social support enhances life satisfaction for females as they transition to self-employment and beyond. These findings confirm that gender has an important influence on support-relevant social interactions, thereby affecting the seeking and giving of social support in personal relations (Matud et al., 2003). Female entrepreneurs appear to be opportunistic in the way they leverage their social support and mobilise resources within their network, especially during stressful events such as launching a new business venture (Johansson et al., 2016).

Policy-makers interested in promoting entrepreneurship and improving entrepreneur well-being outcomes should adopt a customised approach based on gender. Furthermore, they need to focus on the quality of entrepreneur social relationships and aim at influencing would-be entrepreneur’s mind-sets, since PSS is a cognitive assessment of the existence of the supportive network. Accordingly, the development of socialisation programs that target female entrepreneurs developing their feelings of relatedness and social connection could potentially improve their life satisfaction.

Our findings have practical implications for entrepreneurs too. Since PSS is a strong buffering mechanism that helps mitigate job demands, entrepreneurs need to be proactive in building a strong network. Stakeholders in the entrepreneurship ecosystems and educators can play a significant role by helping entrepreneurs overcome the sense of loneliness and isolation during their venture creation. The emergence of co-working spaces that allow entrepreneurs to work alongside their peers, to share different business ideas, and to network with a variety of stakeholders is a step in the right direction to develop social support.

There are a number of limitations in this study. Firstly, as in all panel studies, sample attrition is inevitable, and selection bias might occur. Nevertheless, we tried to overcome this limitation by using LGCM modelling, a technique that has tolerance to missing values (Preacher et al., 2008). Additionally, since the research focuses on five years after the transition to self-employment, a potential sampling bias might arise. The entrepreneurs who survive the first five years are those who may have a strong positive perception about their network support. Secondly, although our study was based on a large and diverse sample of Australians, the generalisability of the research findings may be problematic. Future research needs to verify to
what extent these results can be extrapolated to other contexts within different cultural and institutional frameworks. Thirdly, PSS in HILDA is a unidimensional scale, capturing mainly emotional social support. Future research may explore a different mode of social support, such as instrumental or financial support, which may have different effects on an individual’s life satisfaction. Another research avenue might be to rely on a richer data set to provide a more granular picture of the impact of PSS during the transition into self-employment. Ethnographic studies drawing on in-depth interviews with key informants, observations or diary studies might provide further insight about how entrepreneurs mobilise their social network to help them weather through the ups and downs during start-up and remain happy.

Acknowledgement
The author thanks the editor and two anonymous referees of this journal, as well as Doina Olaru for considered and constructive comments and assistance in the preparation of this article.

References


Appendix

Table 1: Factor loading results for perceived social support (PSS) construct

<table>
<thead>
<tr>
<th>Items</th>
<th>Factor loading</th>
<th>Uniqueness</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 There is someone who can always cheer me up when I’m down</td>
<td>0.7269</td>
<td>0.4716</td>
</tr>
<tr>
<td>2 I seem to have a lot of friends</td>
<td>0.4976</td>
<td>0.7524</td>
</tr>
<tr>
<td>3 I enjoy the time I spend with the people who are important to me</td>
<td>0.5132</td>
<td>0.7366</td>
</tr>
<tr>
<td>4 When I need someone to help me out, I can usually find someone</td>
<td>0.7383</td>
<td>0.4549</td>
</tr>
<tr>
<td>5 When something is on my mind, just talking with the people I know can make me feel better</td>
<td>0.5583</td>
<td>0.6883</td>
</tr>
<tr>
<td>6 I often need help from other people but can’t get it (R)</td>
<td>0.5727</td>
<td>0.6720</td>
</tr>
<tr>
<td>7 People don’t come to visit me as often as I would like (R)</td>
<td>0.7339</td>
<td>0.4614</td>
</tr>
<tr>
<td>8 I don’t have anyone that I can confide in (R)</td>
<td>0.5611</td>
<td>0.6852</td>
</tr>
<tr>
<td>9 I have no one to lean on in times of trouble (R)</td>
<td>0.4496</td>
<td>0.7978</td>
</tr>
<tr>
<td>10 I often feel very lonely (R)</td>
<td>0.5803</td>
<td>0.6633</td>
</tr>
</tbody>
</table>

Note: R = reverse coded item, pooled data over the seven waves of the HILDA survey (n=6,490).

Figure 1: Conceptual model

Note: PSS= perceived social support, L= life satisfaction, t0 -t6 represent time measurements.

The factor loading is fixed to1, and the slope loading varied in each model specified.
Table 2: Demographic characteristics of the sample

<table>
<thead>
<tr>
<th>Sample size</th>
<th>One year before the transition n=1303</th>
<th>Transition year n=1085</th>
<th>One year after the transition n=910</th>
<th>Two years after the transition n=756</th>
<th>Three years after the transition n=617</th>
<th>Four years after the transition n=516</th>
<th>Five years after the transition n=516</th>
</tr>
</thead>
<tbody>
<tr>
<td>Age</td>
<td>M (SD) or %</td>
<td>M (SD) or %</td>
<td>M (SD) or %</td>
<td>M (SD) or %</td>
<td>M (SD) or %</td>
<td>M (SD) or %</td>
<td>M (SD) or %</td>
</tr>
<tr>
<td>39 (12.0)</td>
<td>40 (11.9)</td>
<td>41 (11.8)</td>
<td>42 (11.5)</td>
<td>44 (11.8)</td>
<td>44 (11.75)</td>
<td>45 (11.34)</td>
<td></td>
</tr>
<tr>
<td>Sex</td>
<td>Male</td>
<td>Male</td>
<td>Male</td>
<td>Male</td>
<td>Male</td>
<td>Male</td>
<td>Male</td>
</tr>
<tr>
<td>Male</td>
<td>846 (64.9%)</td>
<td>846 (64.9%)</td>
<td>710 (65.4%)</td>
<td>591 (64.3%)</td>
<td>486 (64.2%)</td>
<td>395 (64.0%)</td>
<td>340 (65.8%)</td>
</tr>
<tr>
<td>Marital status</td>
<td>Married</td>
<td>Married</td>
<td>Married</td>
<td>Married</td>
<td>Married</td>
<td>Married</td>
<td>Married</td>
</tr>
<tr>
<td>Married 758 (58.2%)</td>
<td>758 (58.2%)</td>
<td>660 (60.8%)</td>
<td>586 (63.9%)</td>
<td>493 (65.2%)</td>
<td>412 (66.8%)</td>
<td>339 (65.7%)</td>
<td></td>
</tr>
<tr>
<td>Divorced or Separated</td>
<td>334 (27.8%)</td>
<td>348 (26.7%)</td>
<td>280 (25.8%)</td>
<td>243 (26.5%)</td>
<td>184 (24.3%)</td>
<td>149 (24.2%)</td>
<td>123 (23.8%)</td>
</tr>
<tr>
<td>Single 200 (16.7%)</td>
<td>197 (15.1%)</td>
<td>145 (13.4%)</td>
<td>89 (9.6%)</td>
<td>79 (10.5%)</td>
<td>56 (9.0%)</td>
<td>54 (10.5%)</td>
<td></td>
</tr>
<tr>
<td>Income (log)</td>
<td>10.43 (2.1)</td>
<td>10.15 (3.2)</td>
<td>9.70 (3.9)</td>
<td>9.86 (3.8)</td>
<td>10.04 (3.4)</td>
<td>10.25 (2.9)</td>
<td>10.32 (3.1)</td>
</tr>
<tr>
<td>Education completed</td>
<td>Postgraduate</td>
<td>Undergraduate</td>
<td>Vocational</td>
<td>Year 12 and bellow</td>
<td>Long-term health condition</td>
<td>Present of children</td>
<td></td>
</tr>
<tr>
<td>177 (13.6%)</td>
<td>179 (13.7%)</td>
<td>153 (14.1%)</td>
<td>134 (14.6%)</td>
<td>112 (14.8%)</td>
<td>93 (15.1%)</td>
<td>71 (13.8%)</td>
<td></td>
</tr>
<tr>
<td>347 (26.6%)</td>
<td>353 (27.1%)</td>
<td>295 (27.2%)</td>
<td>250 (27.2%)</td>
<td>213 (28.2%)</td>
<td>165 (26.7%)</td>
<td>136 (26.4%)</td>
<td></td>
</tr>
<tr>
<td>381 (29.2%)</td>
<td>396 (30.4%)</td>
<td>333 (30.7%)</td>
<td>272 (29.6%)</td>
<td>218 (28.8%)</td>
<td>178 (28.9%)</td>
<td>150 (29.1%)</td>
<td></td>
</tr>
<tr>
<td>398 (30.6%)</td>
<td>375 (28.8%)</td>
<td>304 (28.0%)</td>
<td>262 (28.5%)</td>
<td>213 (28.2%)</td>
<td>181 (29.3%)</td>
<td>159 (30.8%)</td>
<td></td>
</tr>
<tr>
<td>Yes 196 (15.0%)</td>
<td>197 (15.0%)</td>
<td>173 (15.9%)</td>
<td>148 (16.1%)</td>
<td>144 (19.0%)</td>
<td>110 (17.8%)</td>
<td>107 (20.7%)</td>
<td></td>
</tr>
<tr>
<td>Present of children</td>
<td>No children ever</td>
<td>Yes 196 (15.0%)</td>
<td>197 (15.0%)</td>
<td>173 (15.9%)</td>
<td>148 (16.1%)</td>
<td>144 (19.0%)</td>
<td>110 (17.8%)</td>
</tr>
<tr>
<td>No children ever</td>
<td>458 (35.1%)</td>
<td>414 (31.7%)</td>
<td>317 (29.2%)</td>
<td>230 (25.0%)</td>
<td>169 (22.3%)</td>
<td>130 (21.0%)</td>
<td>106 (20.5%)</td>
</tr>
</tbody>
</table>

Note: Data pooled across 16 waves from HILDA dataset, and set at the around the baseline (the transition year).
Table 3: Differences between the retained and excluded individuals, established on the baseline (the transition year) demographics

<table>
<thead>
<tr>
<th></th>
<th>Retained (n=1,303)</th>
<th>Excluded (n=870)</th>
<th>$\chi^2$ or $t$</th>
<th>p-value</th>
<th>Cohen's d</th>
<th>[95% Conf. Interval]</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Age</strong></td>
<td>40 (11.9)</td>
<td>36.83 (13.21)</td>
<td>2.553</td>
<td>0.010</td>
<td>0.110</td>
<td>0.025 - 0.196</td>
</tr>
<tr>
<td><strong>Sex (Male)</strong></td>
<td>64.9%</td>
<td>57.8%</td>
<td>9.269</td>
<td>0.002</td>
<td>-0.132</td>
<td>-0.217 - -0.047</td>
</tr>
<tr>
<td><strong>Marital status</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Married</td>
<td>58.2%</td>
<td>53.8%</td>
<td>18.472</td>
<td>0.000</td>
<td>0.102</td>
<td>0.086 - 0.257</td>
</tr>
<tr>
<td>Widowed, divorced or separated</td>
<td>26.7%</td>
<td>27.0%</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Single</td>
<td>15.1%</td>
<td>19.2%</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Income (log)</strong></td>
<td>10.15 (3.2)</td>
<td>9.82 (3.22)</td>
<td>2.961</td>
<td>0.003</td>
<td>0.128</td>
<td>0.043 - 0.213</td>
</tr>
<tr>
<td><strong>Education completed</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Postgraduate</td>
<td>13.7%</td>
<td>9.0%</td>
<td>10.949</td>
<td>0.012</td>
<td>-0.131</td>
<td>-0.217 - -0.045</td>
</tr>
<tr>
<td>Undergraduate</td>
<td>27.1%</td>
<td>24.9%</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Vocational</td>
<td>30.4%</td>
<td>26.4%</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Year 12 and below</td>
<td>28.8%</td>
<td>39.7%</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Long-term health condition (Yes)</strong></td>
<td>15.0%</td>
<td>16.2%</td>
<td>1.688</td>
<td>0.194</td>
<td>0.056</td>
<td>-0.028 - 0.1428</td>
</tr>
<tr>
<td><strong>Presence of children (No)</strong></td>
<td>31.7%</td>
<td>42.4%</td>
<td>7.042</td>
<td>0.080</td>
<td>-0.115</td>
<td>-0.200 - -0.030</td>
</tr>
</tbody>
</table>
Figure 2: The sample average of perceived social support (PSS) over time, presented overall (a) and by gender (b) (n=1,303 unbalanced panel)
Figure 3: The sample average life satisfaction over time, presented overall (a) and by gender (b) (n=1,303 unbalanced panel)
Table 4: Goodness of fit for model comparison

<table>
<thead>
<tr>
<th>Social support</th>
<th>$\chi^2$ (DF)</th>
<th>Compared With:</th>
<th>$\chi^2$ (DF)</th>
<th>p-value</th>
<th>AIC</th>
<th>RMSEA</th>
<th>TLI</th>
<th>CFI</th>
</tr>
</thead>
<tbody>
<tr>
<td>Free LGCM</td>
<td>27.588 (18)</td>
<td></td>
<td>61.588</td>
<td>0.020</td>
<td>0.997</td>
<td>0.996</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Linear LGCM$^A$</td>
<td>36.245 (23)</td>
<td>linear vs free</td>
<td>8.657 (5)</td>
<td>0.124</td>
<td>60.245</td>
<td>0.021</td>
<td>0.995</td>
<td>0.996</td>
</tr>
<tr>
<td>Nonlinear LGCM</td>
<td>45.636 (23)</td>
<td>Quadratic vs free</td>
<td>18.048 (5)</td>
<td>0.003</td>
<td>69.636</td>
<td>0.027</td>
<td>0.993</td>
<td>0.992</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Life Satisfaction</th>
<th>$\chi^2$ (DF)</th>
<th>Compared With:</th>
<th>$\chi^2$ (DF)</th>
<th>p-value</th>
<th>AIC</th>
<th>RMSEA</th>
<th>TLI</th>
<th>CFI</th>
</tr>
</thead>
<tbody>
<tr>
<td>Free LGCM$^A$</td>
<td>35.579 (19)</td>
<td></td>
<td>64.269</td>
<td>0.022</td>
<td>0.993</td>
<td>0.996</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Linear LGCM</td>
<td>42.186 (23)</td>
<td>linear vs free</td>
<td>6.607 (4)</td>
<td>0.158</td>
<td>59.579</td>
<td>0.020</td>
<td>0.994</td>
<td>0.995</td>
</tr>
<tr>
<td>Nonlinear LGCM</td>
<td>43.893 (23)</td>
<td>Quadratic vs free</td>
<td>1.707 (4)</td>
<td>0.789</td>
<td>67.893</td>
<td>0.026</td>
<td>0.999</td>
<td>0.992</td>
</tr>
</tbody>
</table>

Note: $^A$ model with the best model-data fit.

LGCM= latent growth curve model, df= degrees of freedom, AIC= Akaike Information Criterion, RMSEA= root mean square error of approximation, TLI= Tucker-Lewis fit index, CFI= comparative fit index. In all models, invariant residual variance was assumed.
Figure 4: The trajectory of life satisfaction with the intercept and freely estimated slope by gender

Note: Estimated average life satisfaction at $i$ wave = mean intercept + (mean slope x unstandardized factor loading at ($i$) wave)
Table 5: Results of the two parallel process models

<table>
<thead>
<tr>
<th></th>
<th>Model A</th>
<th>Model B</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$\beta$ (S.E)</td>
<td>$\beta$ (S.E)</td>
</tr>
<tr>
<td>Effect of the initial of PSS on life satisfaction</td>
<td>0.555 *** (0.038)</td>
<td>0.555 *** (0.038)</td>
</tr>
<tr>
<td>Effect of the changes of PSS on the changes of life satisfaction</td>
<td>0.680 *** (0.959)</td>
<td>0.680 *** (0.959)</td>
</tr>
<tr>
<td>Effect of the initial of PSS on the changes of life satisfaction</td>
<td>-0.056 *** (0.036)</td>
<td></td>
</tr>
</tbody>
</table>

Model fit indices

<table>
<thead>
<tr>
<th></th>
<th>Model A</th>
<th>Model B</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\chi^2$</td>
<td>233.452</td>
<td>198.901</td>
</tr>
<tr>
<td>df</td>
<td>99</td>
<td>98</td>
</tr>
<tr>
<td>TLI</td>
<td>0.974</td>
<td>0.981</td>
</tr>
<tr>
<td>CFI</td>
<td>0.979</td>
<td>0.984</td>
</tr>
<tr>
<td>RMSEA</td>
<td>0.032</td>
<td>0.028</td>
</tr>
<tr>
<td>AIC</td>
<td>305.452</td>
<td>272.901</td>
</tr>
</tbody>
</table>

Note: Models are nested. $\beta =$ Standardized coefficients; S.E = Standard error; df= degrees of freedom, TLI= Tucker-Lewis fit index, CFI= comparative fit index, RMSEA= root mean square error of approximation, AIC= Akaike Information Criterion. The models are controlling for age at the baseline. Other sociodemographic controls have been tested and results of the structural part of the model did not change significantly. These results are available upon request from authors. Significance: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$
Table 6: Results of the two parallel process models by gender

<table>
<thead>
<tr>
<th>Effect of the initial i of PSS on life satisfaction</th>
<th>Male: β (S.E)</th>
<th>Female: β (S.E)</th>
<th>Model A</th>
<th>Male: β (S.E)</th>
<th>Female: β (S.E)</th>
<th>Model B</th>
<th>Male: β (S.E)</th>
<th>Female: β (S.E)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Effect of the initial i of PSS on life satisfaction</td>
<td>0.573 *** (0.049)</td>
<td>0.516 *** (0.063)</td>
<td>Model A</td>
<td>Male: β (S.E)</td>
<td>Female: β (S.E)</td>
<td>Model B</td>
<td>Male: β (S.E)</td>
<td>Female: β (S.E)</td>
</tr>
<tr>
<td>Effect of the changes of PSS s on the changes of life satisfaction</td>
<td>0.555 *** (0.894)</td>
<td>0.516 *** (0.097)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Effect of the initial i of PSS on the changes of life satisfaction</td>
<td>-0.028 (0.045)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

**Model fit indices**

<table>
<thead>
<tr>
<th>χ²</th>
<th>df</th>
<th>TLI</th>
<th>CFI</th>
<th>RMSEA</th>
<th>AIC</th>
</tr>
</thead>
<tbody>
<tr>
<td>312.352</td>
<td>198</td>
<td>0.978</td>
<td>0.982</td>
<td>0.021</td>
<td>456.352</td>
</tr>
<tr>
<td>311.162</td>
<td>196</td>
<td>0.978</td>
<td>0.982</td>
<td>0.021</td>
<td>459.162</td>
</tr>
</tbody>
</table>

Note: Models are nested. β = Standardized coefficients; S.E = Standard error; df= degrees of freedom, TLI= Tucker-Lewis fit index, CFI= comparative fit index, RMSEA= root mean square error of approximation, AIC= Akaike Information Criterion. The models are controlling for age at the baseline. Other sociodemographics have been tested and results of the structural part of the model did not change significantly; these results are available upon request from authors. Significance: *** p < 0.001, ** p < 0.01, * p < 0.05