The Impact of Unemployment on Cognitive, Affective and Eudaimonic Well-Being Facets: Investigating Immediate Effects and Short-Term Adaptation

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Analysis scripts and full model results can be found in the online repository of the study at https://osf.io/jfms4. The data of the German Job Search Panel (GJSP) is available for researchers upon request.

The authors made the following contributions:

Mario Lawes: Conceptualization, Data Curation, Formal Analysis, Investigation, Methodology, Project administration, Visualization, Writing-Original Draft Preparation, Writing - Review & Editing; ***Clemens Hetschko***: Conceptualization, Funding acquisition, Investigation, Methodology, Project administration, Supervision, Writing—review and editing ***Ronnie Schöb***: Conceptualization, Funding acquisition, Project administration, Writing—review and editing; ***Gesine Stephan***: Conceptualization, Funding acquisition, Project administration, Writing—review and editing; ***Michael Eid***: Conceptualization, Funding acquisition, Methodology, Project administration, Supervision, Writing—review and editing.

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Abstract

While long-lasting declines in life satisfaction following unemployment have been well documented, evidence on the impact of unemployment on affective and eudaimonic well-being is scarce. Moreover, most existing studies relied on yearly panel data and were unable to separate the immediate effects of entering unemployment from prospective effects occurring before individuals become unemployed.

The present study identified the immediate effects of entering unemployment on cognitive, affective and eudaimonic well-being facets using a control-group design based on monthly panel data of initially employed German jobseekers who were at high risk of losing their job. In order to investigate patterns of short-term adaptation, the study further examined whether average well-being levels change within the first months of unemployment using a mixed-effects trait-state-occasion model. All effects were separately computed for jobseekers affected by mass-layoffs or plant closures and individuals who registered as jobseekers due to other reasons. Multi-item instruments and experience sampling were used to validly measure the various well-being facets.

The results indicate that *life satisfaction* and *income satisfaction* significantly decreased for individuals affected by mass-layoffs or plant closures from the last month in employment to the first month in unemployment. For individuals who registered as jobseekers due to other reasons, these effects were smaller and not significant in the case of *life satisfaction*. Crucially, there were no immediate effects of entering unemployment on the examined affective and eudaimonic well-being facets. Moreover, well-being levels were generally stable within the first months of unemployment indicating a general absence of short-term adaptation.

Keywords: unemployment, subjective well-being, eudaimonia, adaptation, experience sampling

The Impact of Unemployment on Cognitive, Affective and Eudaimonic Well-Being Facets: Investigating Immediate Effects and Short-Term Adaptation

Life events can have a drastic impact on people's feelings and life satisfaction (Luhmann et al., 2012). Involuntary job-loss is a work-related life event that occurs rather frequently in our society. Existing research on the impact of unemployment has often focused on life satisfaction (i.e., overall evaluation of one's life) and the satisfaction with specific life domains (e.g., income satisfaction). In the following, we will refer to these evaluative well-being facets as cognitive well-being (CWB). Studies based on large-scale panel data indicated that becoming unemployed is associated with a significant decrease in life satisfaction from the last year in employment to the first year in unemployment (e.g., Clark et al., 2008; Luhmann et al., 2013). Interestingly, previous research further suggested that life satisfaction levels of individuals entering unemployment are already decreased years prior to the job-loss (Clark et al., 2008; Luhmann et al., 2013) and do generally not return to the pre-unemployment levels, even after re-gaining employment (Clark et al., 2001; Hetschko et al., 2019). However, due to the rather long time intervals between measurement occasions (e.g., one year) in most available panel studies, not much is known about the well-being dynamics in close proximity to entering unemployment.

Besides CWB, affective well-being (AWB) and eudaimonic well-being (EWB) facets also seem to play a central role for one's quality of life (Diener, 1984; OECD, 2013; Ryff, 1989). AWB refers to the presence of pleasant affect and the absence of unpleasant affect (Diener, 1984; Larsen & Eid, 2008). AWB and CWB resemble *hedonic* well-being facets and are together often summarized as subjective well-being (SWB; Diener, 1984). Empirical studies underlined that AWB and CWB are distinct constructs that differ in their stability over time (Eid & Diener, 2004), their relations with other variables (Lucas et al., 1996) and their sensitivity towards life events (Luhmann et al., 2012). Conversely, the concept of eudaimonia goes back to Aristotle's Nicomachean Ethics (Aristotle, 2001) and defines well-being as living a good and virtuous life and striving for the best in us (Deci & Ryan, 2008; OECD, 2013; Ryff, 2014). Research on the relationship between EWB and SWB facets is mixed. Some studies indicated that EWB and SWB facets differ in terms of temporal stability (Ryff et al., 2015) and their associations with other variables (Ryff, 1989), whereas other researchers have questioned the validity of distinguishing between SWB and EWB facets due to conceptual (Kashdan et al., 2008) or empirical reasons (Disabato et al., 2016; Goodman et al., 2018). Longitudinal studies contrasting the impact of unemployment on CWB, AWB and EWB facets are currently lacking.

The first goal of this study is to examine how cognitive, affective and eudaimonic well-being facets change from the last month in employment to the first month in unemployment. We identify these *immediate* effects of unemployment using a control group design based on the first two waves of the German Job Search Panel (GJSP; Hetschko, Eid, et al., 2020), a monthly panel study of initially employed German jobseekers who were at high risk of losing their jobs. The research design allows isolating the immediate effects of entering unemployment from prospective effects occurring in the weeks and months prior to the job-loss and addresses the question whether the *actual transition into unemployment* still affects well-being even when individuals have already *expected* to become unemployed.

The second aim of this study is to examine whether individuals adapt to being unemployed within the first months of unemployment. Based on all monthly waves of the GJSP, we examine adaptation patterns by contrasting the immediate effects of unemployment that occur within the first month of unemployment to the effects occurring when individuals are unemployed for multiple months. A better understanding of the timing and strength of the effects of unemployment on the various well-being facets will help to determine critical time periods for individuals facing unemployment. These insights can then support policy makers and practitioners (e.g., job search advisors) in designing effective regulations and interventions that promote the well-being of jobseekers.

We begin this article by summarizing the existing research on the impact of unemployment on cognitive, affective and eudaimonic well-being facets. Then, we describe the aims and contributions of the article before presenting the methods and results. Lastly, we discuss our findings in the context of the existing literature and derive implications for future studies.

Effects of Unemployment on Cognitive Well-Being

The impact of unemployment on CWB has been studied extensively (e.g., Clark et al., 2008; Gerlach & Stephan, 1996; Kassenboehmer & Haisken-DeNew, 2009; Lucas et al., 2004; Luhmann et al., 2014; Luhmann & Eid, 2009; Winkelmann & Winkelmann, 1998). Meta-analytical findings of prospective longitudinal studies revealed that unemployment has a negative medium-sized effect (d = -0.43) on CWB (Luhmann et al., 2012). The negative effects in terms of life satisfaction seem to be long-lasting and some empirical research even indicated that unemployed individuals on average do not return to their pre-unemployment life satisfaction levels after regaining employment ("scarring effect", see Clark et al., 2001; Hetschko et al., 2019; in contrast to Zhou et al., 2019).

Further, prospective studies revealed that the average level of life satisfaction is already decreased years before becoming unemployed (e.g., Clark et al., 2008; Luhmann et al., 2013). In particular, shattered future expectations and uncertainty seem to play an enormous role in the effects of unemployment on life satisfaction (Clark et al., 2010). For instance, previous research indicated that unemployed people with good re-employment prospects are more satisfied with their lives than employed people who consider themselves at high risk of losing their job (Knabe & Rätzel, 2010). Thus, it is likely that the strong negative prospective effects of unemployment on CWB facets can be explained by growing job insecurity before a job loss. Additionally, this finding raises the question whether the actual transition into unemployment from an already highly insecure job reduces cognitive well-being even further.

Research on domain-specific satisfaction showed that the satisfaction with one's job and finances is already decreased one year before a job-loss and remains low during unemployment (Chadi & Hetschko, 2017; Powdthavee, 2012). Moreover, the satisfaction with one's social life seems to be decreased even multiple years *after* becoming unemployed (Powdthavee, 2012). However, losing one's job also seems to increase the average satisfaction with one's family life and leisure time, probably because unemployment frees up time for family and leisure activities (Chadi & Hetschko, 2017).

Effects of Unemployment on Affective Well-Being

Meta-analytical findings of prospective studies showed that on average unemployment has a negative effect on AWB, in a magnitude that does not statistically differ from the effect of unemployment on CWB (Luhmann et al., 2012). Unlike the studies investigating CWB, the effect sizes for AWB vary considerably across studies (d = -1.09 to d = 0.66) showing that some studies indicated a strong increase in AWB following unemployment whereas other studies showed a steep decrease in AWB (Luhmann et al., 2012). These divergent results are likely due to differences in terms of study population (e.g., long-term unemployed vs. transition into re-employment), instruments used to measure AWB (e.g., momentary mood assessment vs. retrospective mood assessment) and data analysis methods.

In panel studies, AWB has been assessed with a wide range of instruments. Often, individuals were asked to recall how they felt during the last two or four weeks. Studies based on these retrospective assessments of AWB indicated that becoming unemployed is associated with small but persistent increases in sadness, small decreases in happiness seven to nine months after becoming unemployed, small increases in anxiety in the first months after becoming unemployed and no changes in anger (von Scheve et al., 2017). Moreover, negative mood was found to be increased and positive mood to be decreased for up to three years before and after experiencing a job-loss (Hentschel et al., 2017).

Retrospective assessments of AWB offer important insights into the individual reconstruction of affective experiences. However, they are prone to recall biases. Therefore it is often favorable to measure AWB using the experience sampling method (ESM, Hektner et al., 2007), where individuals are asked to indicate their momentary affective states via pagers or smartphones (OECD, 2013), or to combine the ESM with retrospective assessments. As the ESM is rather difficult to implement, empirical studies investigating the effects of unemployment on AWB using ESM are scarce. Bryson and MacKerron (2017) found in a large UK-based ESM study that being at work reduces happiness by about 8 percentage points (p.p.) compared to other activities.

As a viable alternative to the ESM, Kahnemann et al. (2004) developed the day reconstruction method (DRM). In the DRM, respondents are asked to define distinct activity episodes of the past day and to rate their affective states during each episode.[1] Knabe et al. (2010) used the DRM in a cross-sectional study to compare AWB of unemployed and employed individuals. They found that unemployed indviduals experience more negative relative to positive emotions when compared to employed individuals during the same activities. The authors termed this phenomenon the *saddening effect*. At the same time, unemployed individuals seem to spend more time engaging in generally pleasant activities than employed indviduals (Kahneman et al., 2004; Knabe et al., 2010), which has been termed the *time composition effect*. Several DRM studies did not find any differences between employed and unemployed individuals in terms of time-weighted measures of AWB, which has often been explained by an interplay between the saddening effect and the time composition effect (Dolan et al., 2017; Knabe et al., 2010). Other DRM studies suggested that unemployed individuals are significantly sadder, more often in pain, experience similar levels of happiness, stress and tiredness (Krueger & Mueller, 2012) and have higher levels of enjoyment (Hoang & Knabe, 2020; Wolf et al., 2019) compared to employed individuals.

[1] A recent study directly comparing the ESM and the DRM, revealed that the DRM and the ESM do not provide the same results as the DRM seems to be more influenced by individual expectations (Lucas et al., 2021).

Overall, the extant evidence from studies that are less prone to recall bias does not confirm negative effects of unemployment on AWB.

Effects of Unemployment on Eudaimonic Well-Being

In the psychological literature, many different definitions and conceptualizations of EWB exist (for an overview see Heintzelman, 2018). A prominent theory of EWB is Carol Ryff's (1989) taxonomy of psychological well-being, which is based on various theoretical models from developmental, clinical, existential and humanistic psychology. The concept of psychological well-being consists of the following six dimensions: *autonomy*, *environmental mastery*, *personal growth*, *positive relations with others*, *purpose in life* and *self-acceptance* (Ryff, 1989, 2014). Moreover, a large body of research on the experience of *meaning in life* evolved independent of Ryff's framework (Heintzelman, 2018). Another influential EWB theory is the self-determination theory (SDT; Deci & Ryan, 2000; Ryan & Deci, 2001). SDT also considers self-realization as a key element of human well-being and posits that fulfilling the three psychological needs *autonomy*, *competence* and *relatedness* is essential for achieving eudaimonia (Ryan & Deci, 2001). An important difference between SDT and Ryff's theory of psychological well-being is that Ryff's theory directly defines EWB using the six described dimensions, whereas SDT outlines psychological needs that foster rather than define well-being (Heintzelman, 2018; Ryan & Deci, 2001).

Unfortunately, there is a lack of studies investigating the impact of unemployment on EWB facets. Some evidence for the role of employment for EWB comes from studies investigating the relationship between job-characteristics and perceived meaningfulness of one's job. These studies indicated that jobs that provide *professional autonomy*, *supportive social relationships with colleagues* and *societal impact* are perceived as most meaningful (Bryce, 2018; Nikolova & Cnossen, 2020). Further, having a meaningful job was found to be negatively correlated with intentions to retire and absenteeism (Nikolova & Cnossen, 2020). DRM data indicated that being at work provides individuals with higher levels of meaning compared to many other activities even if it is not perceived as pleasurable (White & Dolan, 2009; Wolf et al., 2019). More evidence for the importance of EWB in the context of employment comes from an extensive case-study by Synard and Gazzola (2017) who studied 20 Canadians who had involuntarily lost their jobs in the technology sector between 2000 and 2006. Based on unstructured written narratives, the authors identified six well-being themes that were perceived as being important during a job-loss. Three of these themes are closely linked to CWB (*life evaluation*), AWB (*transitory experiencing*) and mental health (*mental ill-being/ ill-health*). The remaining three themes termed *growth and grounding*, *environmental mastery and stability* and *motivational mindsets and conditions* clearly resemble EWB facets (Synard & Gazzola, 2017).

Despite the lack of rigorous empirical investigations of the effects of unemployment on EWB, eudaimonic concepts are defining features of several influential theories on the effects of unemployment on well-being. Marie Jahoda's latent deprivation model (1982), for example, posits that paid employment provides employees access to the following six psychological needs: *imposition of a time structure*, *social activities outside of the closer family circle*, *participation in a collective purpose*, *status*, *identity* and *regular activity* (Jahoda, 1982, p. 59).[2] The latent deprivation model states that individuals suffer during unemployment because they are unable to fully satisfy these psychological needs without paid employment (Jahoda, 1982). Empirical evidence for the latent deprivation model comes from multiple cross-sectional (e.g., Paul et al., 2009; Paul & Batinic, 2010) and longitudinal studies (e.g., Hoare & Machin, 2010; Zechmann & Paul, 2019). Interestingly, several of Jahoda's latent functions of employment closely resemble eudaimonic concepts. Specifically, the latent function of *participation in a collective purpose* is closely linked to the dimension *purpose in*

[2] In a similar vein, Warr's (1987) vitamin model theorizes nine environmental factors that are provided by paid employment, namely *opportunity for control*, *opportunity for skill use*, *externally generated goals*, *variety*, *environmental clarity*, *availability of money*, physical security, *opportunity for interpersonal contact*, and *valued social position*.

life of Ryffs's model. Moreover, the latent functions *social activities* and *imposition of a time structure* are closely linked to the dimensions *positive relations with others* and *environmental mastery* of Ryff's model.

Additional theoretical support for the relevance of eudaimonic concepts in the context of employment research comes from Fryer's (1986) agency restriction model. This model posits that humans are "agents actively striving for purposeful self-determination, attempting to make sense of, initiate, influence, and cope with events in line with personal values, goals, and expectations of the future" (Fryer, 1997, p. 12). According to the agency restriction model, these human agentic features are severely deterred during unemployment due to poverty and insecurity about the future, which results in low well-being. The incongruence model by Paul and Moser (2006) similarly assumes that (a) individuals have a strong preference to work and (b) unemployed individuals have lower well-being because they cannot attain their employment-related goals. Evidence for the incongruence model comes from a cross-sectional study, which demonstrated that unemployed individuals are less able to realize their life goals than employed individuals (Paul et al., 2016). These described empirical studies and theoretical models underline that EWB is an important concept in the context of unemployment, which is unfortunately heavily understudied.

The Present Study

As summarized above, existing longitudinal studies on the effects of unemployment on well-being generally relied on yearly panel data. Thus, the timing and magnitude of the well-being changes occurring in close proximity to a job-loss are largely unknown. In the present study, we use novel monthly panel data of initially employed German jobseekers, who were at risk of losing their job, to address this issue.

In a first step, we investigate whether the *actual transition into unemployment* still affects well-being even when individuals already *expect or know* to become unemployed. For example, it could be the case that most well-being changes occur in the weeks leading up to the job-loss (e.g., lower life satisfaction or sense of purpose when individuals know that they will soon be unemployed) and that the actual transition into unemployment has no immediate effect anymore. In particular, we examine the extent to which various CWB, AWB and EWB facets change from the last month in employment to the first month in unemployment. To isolate those well-being changes that are due to entering unemployment from general well-being changes unrelated to becoming unemployed (e.g., anticipatory effects), we use a control group design based on the first two waves of the GJSP study. Moreover, we focus on individuals that are at high risk of losing their job due to mass-layoffs or plant closures in order to minimize the influence of individual qualifications and characteristics on the probability of a job-loss. We probe the robustness of the results by (a) statistically controlling for differences in employment-related expectations and (b) re-estimating all effects in a propensity score matched sample. We expect that the immediate effects over the course of one month will be smaller compared to the yearly effects reported in existing panel studies as the latter encompass anticipatory effects occurring in the months leading up to the job-loss as well as the effects of becoming and being unemployed for some months. In order to increase external validity we add a further comparison group of individuals having a high risk of losing their job due to reasons other than mass-layoffs or plant closures.

In a second step, we examine whether individuals adapt to being unemployed within the first months of unemployment. For example, for some well-being facets it might be the case that the negative effects of unemployment only evolve after being unemployed for some time. We use monthly panel data to track how the various well-being facets change within the first months of unemployment. This approach allows revealing detailed patterns of short-term adaptation to unemployment.

While most existing studies have focused on the effects of unemployment on CWB facets and the few studies investigating the effects of unemployment on AWB facets have methodological limitations (e.g., cross-sectional data, retrospective assessments of affect), we take a broader view by simultaneously investigating numerous cognitive, affective and eudaimonic well-being facets. Based on the robust finding that unemployment affects CWB facets more strongly than AWB facets (e.g., Knabe et al., 2010), we expect to find stronger immediate effects of entering unemployment for CWB facets compared to AWB facets. The empirical foundation for how EWB facets might be affected by unemployment is poor, which is why we do not derive a clear prediction for EWB facets.

Method

Data

The study was based on the German Job Search Panel (GJSP; Hetschko, Eid, et al., 2020), a longitudinal panel study of German jobseekers. The study was approved on Dec 13, 2017 by the ethics committee of the Department of Education and Psychology at Freie Universität Berlin under the name "The impact of unemployment on various indicators of well-being. An interdisciplinary study of time-varying effects, adaptation and coping strategies based on real-time data" ["Die Auswirkungen der Arbeitslosigkeit auf verschiedene Indikatoren des Wohlbefindens. Eine interdisziplinäre Untersuchung von zeitvariierenden Effekten, Adaptation und Bewältigungsstrategien auf Basis von Echtzeitdaten"].

Institutional Background

In Germany, employees are obliged to register as jobseekers at least three months prior to the day of their expected job-loss in order to be eligible for unemployment benefits. If individuals find out about the termination of their employment at a later time point, they have to register as a jobseeker within three days. Otherwise, a cut-off period for unemployment benefit receipt might apply. Crucially, many individuals who registered as jobseekers do not enter unemployment later on (see Stephan, 2016).

Recruitment Process

From November 2017 to May 2019, 127,836 Germans aged between 18 and 60 who registered as jobseekers in the German unemployment insurance system prior to possibly entering unemployment were invited via mail or e-mail to participate in the GJSP (Hetschko, Eid, et al., 2020; Lawes et al., 2021). 79,710 of the identified jobseekers were likely to be affected by mass-layoffs or plant closures[3] and 48,126 registered as jobseekers from other companies. Invited individuals were asked to fill out an online entry survey to determine their eligibility for the study. Individuals were eligible if they were still employed in the job out of which they registered as jobseekers and if their current employment had lasted for at least six months. This procedure ensured (a) at least one measurement occasion before respondents potentially entered unemployment and (b) that participants passed their probation. Additionally, we randomly excluded one third of all individuals after the entry survey to investigate the role of survey participation on employment related outcomes (Hetschko, Eid, et al., 2020). In total, 4,700 (3.68%) individuals started the entry survey, from which 1,540 (1.20%) could be included in the GJSP sample (see Figure 1 for flowchart).

In sum, during the first measurement occasion of the GJSP all participants were employed jobseekers who were at high risk of losing their job. However, only some of these individuals eventually entered unemployment at a certain wave of the GJSP. Other individuals remained employed throughout the study, for instance because they were not laid off after all or because they immediately found new employment without entering unemployment.

Procedure

[3] Each month during the recruitment period, the Data and IT Management unit (DIM) of IAB identified all registered jobseekers as well as the total number of job seeking registrations from each company. Based on this information, we applied the thresholds for a mass-layoff according to §17(1) of the German employment protection act (*Kündigungsschutzgesetz*). Specifically more than five registrations as jobseekers from plants with 21 to 59 employees, 10% from plants with 60 to 250 employees, more than 25 registrations of jobseekers from plants with 251 to 499 employees and more than 29 registrations as jobseekers from plants with 500 or more employees were considered as mass-layoffs. In addition, we assumed a mass-layoff in for plants with less than 20 employees if more than five people registered as jobseekers.

The survey was carried out via a smartphone app, which was specifically developed by the App Research Organization and runs on Android and iOS (for details on the survey app see Ludwigs & Erdtmann, 2019). Monthly questionnaires were sent to the respondents via the survey app on up to eight consecutive days over the course of up to 24 months. The questionnaires encompassed a wide range of psychological constructs and work-related variables (for a detailed list see Hetschko, Eid, et al., 2020). To ensure continuous participation, respondents received 10 euros for each month within the first year of participation if they submitted at least 80% of all questionnaires and two additional payments of 40 euros after participating for six and twelve months. Instead of receiving the cash incentives, jobseekers could also borrow a smartphone from the study team that was of similar monetary value as the sum of the incentives. By doing so, we made study participation possible for people who had not owned a smartphone before. Participants could keep the smartphone after actively participating in the study for at least one year.

Measures

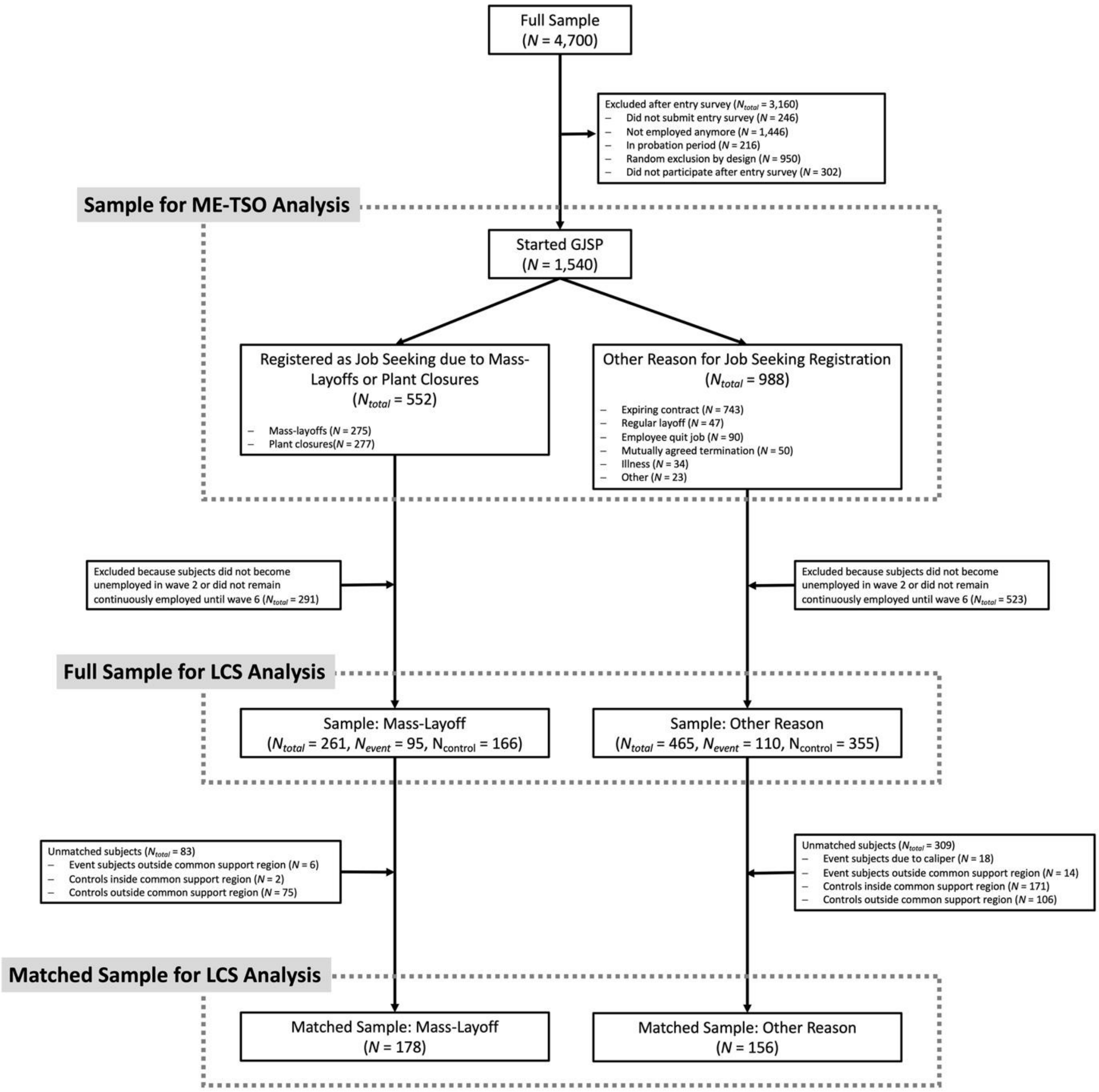
In order to make the scales of the different well-being facets comparable, we transformed all well-being scores into percent of maximum possible scores (POMP; P. Cohen et al., 1999) so that they range from 0 to 100 and can be interpreted in terms of percentage points. Moreover, we reverse coded all negatively worded items before analysis. The wordings for all examined well-being items are presented in Material S2 in the supplementary files.

Employment Status

In each wave of the GJSP, respondents indicated their current employment status based on nine categories (e.g., part- or full-time employed, self-employed, unemployed). We categorized all individuals that are in paid employment or are self-employed as *employed*. Respondents that indicated that they are registered as unemployed and do not participate in any support schemes were categorized as *unemployed*. Moreover, we categorized individuals as *participants of active labor market policies (ALMPs),* when they take part in public subsidy programs or occupational retraining, or as *individuals with other non-employment* if they were in occupational training, school or university, unable to work (i.e., due to illness), retired or used the category “other”.

Figure 1

Participant Flowchart



Note. LCS = latent change score models; ME-TSO = mixed-effects trait-state-occasion model

Cognitive Well-Being

Each month of the survey, life satisfaction was assessed with the Satisfaction With Life Scale (SWLS; Diener et al., 1985). Participants rated five statements such as “I am satisfied with my life.” on a 7-point rating scale ranging from *strongly disagree* (1) to *strongly agree* (7). As items 4 and 5 of the SWLS have been shown to have poorer psychometric properties (Diener et al., 1985; Kjell & Diener, 2021; Pavot & Diener, 2009) and refer to longer time periods (e.g., “If I could live my life over, I would change almost nothing.”) we only used the first three SWLS items. As the reference indicator, we used the third item (“I am satisfied with my life.”). Moreover, we analyzed the domain-specific satisfaction with respect to the following four domains: *activities in the household*, *household income, leisure time* and *family life*. Participants rated their satisfaction with each domain on an 11-point rating scale ranging from *completely dissatisfied* (0) to *completely satisfied* (10). The domain-specific satisfaction items were based on the items used in the Socio-Economic Panel (SOEP; Wagner et al., 2007). At the start of the GJSP these items were administered every three months; starting in December 2018, however, these items were presented monthly. Therefore, the sample size at the second measurement occasion of the GJSP (M2) was smaller for these items compared to the other well-being measures (see Tables S1 – S4 in supplementary materials).

Affective Well-Being

Momentary Mood. On the last day of each monthly survey wave, participants received six short ESM questionnaires at randomly chosen times throughout the day between 8am and 9pm. If respondents completed less than three ESM episodes, the ESM module was repeated two days later. During each ESM episode, respondents received six items from the Multidimensional Mood State Questionnaire (MDSQ; Steyer et al., 1994; Steyer, Schwenkmezger, et al., 1997) to rate how they momentarily feel on a 5-point rating scale ranging from *not at all* (1) to *very much* (5). The MDSQ is a three-dimensional measure of AWB and allows assessing the following mood states: *happy*, *calm* and *awake*. Each AWB dimension was assessed with one positively worded item (e.g., "In the moment I feel happy.") and one negatively worded item (e.g., "In the moment I feel unhappy."). We used the positively worded items as the reference indicators. For each item, we separately averaged the responses across the submitted ESM episodes for a given survey wave. For respondents with less than three submitted episodes in the initial ESM day, we averaged across the ESM measurements obtained from the day with more submitted ESM episodes. In cases where the same number of ESM episodes were submitted on both days, we used the data from the first ESM day.

Mood in Last Week. At each survey wave, participants received a German version of the Center for Epidemiological Studies Depression Scale (for German version [ADS] see Hautzinger, 1988; for original version [CES-D] see Radloff, 1977). In the CES-D, individuals indicate on 15 items how they felt during the past week on a 5-point rating scale ranging from *rarely or none of the time (less than 1 day)* (1), *some or a little of the time (1-2 days)* (2), *occasionally or a moderate amount of time (3-4 days)* (3), *most or all of the time (5-7 days)* (4) to *don't know* (5). For all analyses, the category *don't know* was coded as a missing value. Based on item content, we selected six items from the ADS to define the following three affective well-being facets using two items for each facet: *worried mood* (reference indicator: "I was bothered by things that usually don't bother me."), *sad mood* (reference indicator: "I felt depressed."), *good mood* (reference indicator: "I was happy.").

Eudaimonic Well-Being

Psychological Well-being. Every month of the survey, an adapted 24-item version of a German translation of the Ryff-Scale for Psychological Well-Being (Risch et al., 2005; Ryff, 1989) was used to assess psychological well-being. The 24-item short form was obtained by applying confirmatory factor analysis in combination with an ant algorithm in a large sample of individuals that responded online to the 54-item version of the Ryff-Scale (Schultze, 2017). Each of the six psychological well-being dimensions (i.e., *self-acceptance*, *positive relations with others*, *autonomy*, *environmental mastery*, *personal growth* and *purpose in life*) was measured with four items. Individuals responded on a 4-point rating scale ranging from *completely disagree* (1) to *completely agree* (4). For the present analyses, we excluded all items of the Ryff-Scale that have strong references to the past (e.g., "I gave up trying to make big improvements or changes in my life a long time ago.") to obtain indicators that are sensitive to change. Moreover, we excluded the item "There is truth to the saying that you can't teach an old dog new tricks." because it seems that it was often misunderstood by the respondents. In total, we excluded one item each for the dimensions *positive relations* and *self-acceptance* as well as three items of the dimension *personal growth*. A list of the included and excluded items as well as the information which items were chosen as reference indicators is presented in Material S2 in the supplementary files.

Momentarily Experienced Meaning. Besides psychological well-being, we assessed momentarily experienced meaning as a facet of EWB. At each ESM episode individuals were asked to respond to the questions "My current activity has a deeper meaning." (reference indicator) and "My current activity has no deeper meaning." on a 5-point rating scale ranging from *not at all* (1) to *very much* (5). We averaged the responses analogously to the momentary AWB measures across all ESM episodes of a given day.

Overview of Analytical Strategy

In a first analysis, we identified the effects of entering unemployment that occurred between the last month in employment and the first month in unemployment. In order to validly isolate these *immediate effects* of unemployment, we focused on the first two measurement waves of the GJSP and compared the well-being changes of individuals who entered unemployment (i.e., event group) to the well-being changes of individuals who remained employed but who were initially also at risk of losing their job (i.e., control group). In a second analysis, we examined adaptation patterns by investigating whether the immediate effects that occurred in the first month of unemployment differ from those effects that occurred after multiple months in unemployment. In particular, we used a multi-level modeling framework to derive detailed within-person effects of unemployment based on all measurement occasions of the GJSP. In the following, we describe the two analytical strategies in detail.

Analysis I: Immediate Effects of Unemployment

Examining the immediate effects of unemployment on well-being implies that the potential well-being changes are *caused* by the transition into unemployment. Unfortunately, such causal conclusions are threatened by the fact that life events like "entering unemployment" cannot be studied in randomized experiments. In observational studies like the GJSP, psychologists have traditionally refrained from using causal language (for examples see Grosz et al., 2020). However, as multiple elaborate frameworks for causal inference based on observational data are available (e.g., Pearl, 2000; Rubin, 1974; Steyer, 2005), this taboo has recently been criticized (Grosz et al., 2020; Hernán, 2018; Rohrer, 2018). Designing natural experiments that mimic experimental settings is considered the gold standard method for approximating causal effects in observational studies (Hernán & Robins, 2020). To approximate the causal immediate effects of unemployment on the well-being facets, we therefore defined a natural experiment with an event group of individuals who entered unemployment and a control group of individuals who remained employed.

Sample

Due to the previously described institutional process, in which individuals generally register as jobseekers three months prior to the expected time of entering unemployment, most entries into unemployment in the GJSO are observed between the first measurement occasion (M1) and the second measurement occasion (M2) (see Figure S5 in the supplementary materials). In addition, many individuals who became unemployed between M1 and M2 take up a new job rather soon. In order to isolate the immediate effects of unemployment from other effects (e.g., re-employment) as well as to ensure that the time since the job seeking registration is roughly the same for all individuals, we based our analyses on the first two waves of GJSP data (i.e., directly before and after the event group entered unemployment).

Moreover, in order to derive valid causal effects from natural experiments, the treatment assignment (here: entering unemployment) must be conditionally random (for a review see Craig et al., 2017). A common way to minimize the influence of individual qualifications and characteristics on the probability of losing one's job (i.e., selection effects), is to focus on individuals who lost their jobs due to plant closures or mass-layoffs (see Kassenboehmer & Haisken-DeNew, 2009; Marcus, 2013; Paul & Moser, 2009). The assumption is that for this group of individuals, a potential job-loss is involuntary and unrelated to low productivity or individual characteristics (e.g., personality). Thus, we focused our causal analyses on individuals who reported that they have registered as jobseekers due to mass-layoffs (N = 275) or plant closures (N = 277). However, we also included individuals who registered as jobseekers due to other reasons (N = 988) to contrast the unemployment-related well-being changes between both groups of jobseekers (see Figure 1 for a flowchart). The findings for this latter group need to be interpreted more cautiously given that individual characteristics likely play a major role in the likelihood of entering unemployment in this group (i.e., making the assumption of a conditionally random treatment assignment less plausible). Based on these considerations, we defined the following four groups:

Event Group (Mass-Layoff). Among all individuals who registered as jobseekers due to mass-layoffs or plant closures, 95 entered unemployment between M1 and M2. These individuals were assigned to the *event group mass-layoff*.

Event Group (Other Reason). Individuals who registered as jobseekers due to reasons other than mass-layoffs or plant closures and who entered unemployment between M1 and M2 (N = 110) were assigned to the second event group, which we called *event group* *other reason*.

Control Group (Mass-Layoff). Individuals who registered as jobseekers due to mass-layoffs or plant closures but remained employed - either in the same job as before or with a new employer - throughout the first six waves of the GJSP (*N* = 166) were assigned to the *control group mass-layoff*. We assume that the well-being changes of these individuals resemble the unobserved counterfactual well-being changes of individuals in the *event group mass-layoff*, if they had remained employed.

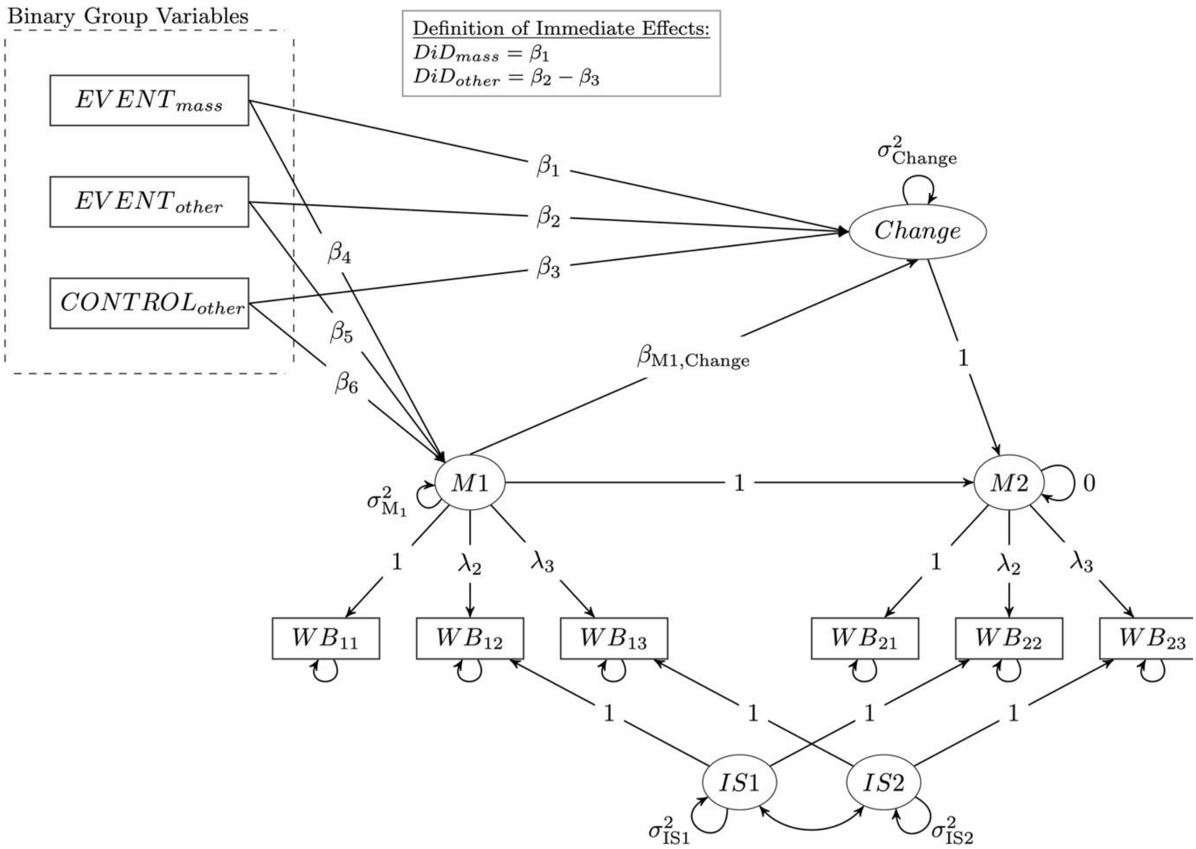
Control Group (Other Reason). Lastly, individuals who registered as jobseekers due to reasons other than mass-layoffs or plant closures and remained employed - either in the same job as before or with a new employer - throughout the first six waves of the GJSP (N = 355) were assigned to the second control group, which we termed *control group other reason*. We assume that the well-being changes of these individuals resemble the unobserved counterfactual well-being changes of individuals in *the event group other reason*, if they had remained employed.

Analytical Strategy

We estimated the immediate effects of unemployment on the well-being facets using a difference-in-differences (DiD) approach (for a review see Wing et al., 2018). Specifically, we specified separate latent change score models (LCS; McArdle & Hamagami, 2001; McArdle & Nesselroade, 1994; Steyer, Eid, et al., 1997; Steyer et al., 2000) for all well-being facets that were assessed with multiple indicators. LCS models allow modeling the true (i.e., error-free) well-being levels at M1 as well as the true intra-individual well-being changes from M1 to M2. In order to account for indicator-specific variance of the non-reference item(s) over time, we included indicator-specific factors (Eid & Kutscher, 2014; Geiser et al., 2010). As future unemployment has been found to affect well-being levels already before the job-loss (e.g., Luhmann et al., 2013; von Scheve et al., 2017) and pre-event well-being levels are likely correlated with subsequent well-being changes, we controlled for the pre-event well-being levels when estimating the average group differences in intra-individual well-being changes. We did so by regressing the well-being changes onto the well-being levels at M1 (McArdle, 2009). An additional advantage of this approach is that it controls for all time-invariant confounding influences when deriving the DiD estimates.

Figure 2

Exemplary Latent Change Score Model with Three Indicators



Note. WB_{11}-WB_{13} resemble well-being indicators at wave 1 (i.e., M1). WB_{21}-WB_{23} resemble well-being indicators at wave 2 (i.e., M2). The factors *IS1* and *IS2* are indicator-specific factors. The factors *M1* and *M2* are the well-being levels at wave 1 and 2. The *Change* factor captures the intra-individual changes from M1 to M2. $EVENT_{mass}$, $EVENT_{other}$ and $CONTROL_{other}$ are dummy variables indicating the group membership (with the *control group mass-layoff* being the reference group).

We defined the *control group mass-layoff* as the reference group and regressed the intra-individual well-being changes occurring between M1 and M2 onto three binary variables indicating the group membership (i.e., $EVENT_{mass}$, $EVENT_{other}$, $CONTROL_{other}$) to obtain the average group differences in the intra-individual well-being changes. Moreover, we regressed the well-being levels at M1 onto these group variables to obtain the average group differences in the pre-event well-being levels. Figure 2 depicts a path diagram for such a model for an exemplary well-being dimension that is assessed with three items (e.g., *life satisfaction*).

Following the notation of Figure 2, the regression weight β_1 captures the differences in the mean well-being changes among the *event group mass-layoff* and the *control group mass-layoff* controlling for individual differences at M1 (i.e., the DiD estimate). The DiD estimate for individuals that registered as job seeking due to other reasons can be obtained by subtracting the regression coefficient β_3 from β_2. For single-item measures (i.e., the domain satisfaction items and *psychological growth*) we used a structurally analogous manifest change model. As a check, we also ran separate LCS models for the *mass-layoff* and *other reason* groups with a single event dummy variable (i.e., event vs. control group).

Measurement Invariance Testing. The application of LCS modeling requires strong measurement invariance (MI) (Steyer et al., 2000). We tested whether the assumption of strong MI holds for all multi-item well-being facets, by fitting separate latent state models with indicator specific factors. We first fitted so-called configural MI models, in which the general measurement structure is set to be equal across time (i.e., the same items load on the same factors across time) but the intercepts, factor loadings and residual variances are freely estimated (Widaman & Reise, 1997). In a second step, we fitted strong MI models, in which the intercepts and factor loadings are constrained to be equal across time. By comparing the fit of the configural and strong MI models, we then determined whether the assumptions of strong MI are justifiable (see Eid & Kutscher, 2014).

Common Trends Assumption. The DiD estimates from the LCS model only correspond to the average *causal* immediate effects of unemployment on the well-being facets, if the average well-being changes in the control groups resemble the counterfactual well-being changes of the event groups, if all individuals in the event groups had remained employed (i.e., common trends assumption; see Wing et al., 2018). Whether or not this common trends assumption holds is, however, not testable. We assume that the common trends assumption is more likely to hold for individuals that are highly similar to each other during M1. Thus, we inspected - separately for each of the two groups of jobseekers - the standardized mean differences (SMDs) between the event and control groups for all variables measured at M1. To compute the SMDs, we used the scale means for multi-item measures (e.g., personality) and binary indicators for heavily skewed variables (e.g., symptom strength of certain diseases). For variables with missing data, we created missing data indicators (MDI) to examine whether the distribution of missing values is balanced in both groups. We used the pooled standard deviation to compute the SMDs for continuous covariates and computed the raw differences for binary variables. We categorized SMD values between -0.25 and 0.25 as satisfactory (Stuart, 2010; Stuart & Rubin, 2008).

Figures S1 and S2 in the supplementary materials illustrate the SMDs and indicate that among individuals from mass-layoffs or plant closures the event and control group were balanced with respect to most variables. However, especially the expectations to “lose one’s job within the next six months” (SMD = 0.69) and to “search for a new job within the next six months” (SMD = 0.42) as well as the *job satisfaction* (SMD = -0.43) differed between the *event group mass-layoff* and the *control group mass-layoff*. This shows that the *event group mass-layoff* and the *control group mass-layoff* were indeed highly similar with respect to many individual characteristics (e.g., coping, personality) at M1 but unsurprisingly differed in terms of their employment-related expectations. The SMDs were more pronounced among individuals that registered as jobseekers due to a different reason than mass-layoffs or plant closures (see Figure S2). This finding indicates that the *event group other reason* and *control group other reason* differed strongly at M1 making the common trends assumption less plausible for these individuals. Because unbalanced variables can potentially confound the causal effect estimation, we ran two robustness checks to investigate the validity of the estimated DiD effects.

Robustness Check I: Controlling for Employment-Related Expectations

The differences in terms of the employment-related expectations between the event and control groups could potentially confound the effect estimates because these employment-related expectations likely resemble real job prospects. Thus, we added the expectations to "lose one's job within the next six months" and to "search for a new job within the next six months" as predictors of the pre-event well-being levels (*M1*) and the well-being changes (*Change*). This way, we analytically controlled for differences in terms of these employment-related expectations. As these expectation variables were not normally distributed, we used three dummy indicators to code different expectations levels (10-50%, 60-90% and 100%, with 0% being the reference category).

Robustness Check II: Propensity Score Matching

Besides the employment-related expectations, several other characteristics potentially threaten the common trends assumption. Thus, as a second robustness check, we aimed at equating the event and control groups in regard to *all* covariates measured at M1 using propensity score matching (PSM; see West et al., 2014). We separately matched individuals from the *event group mass-layoff* to individuals from the *control group mass-layoff* as well as individuals from the *event group other reason* to individuals from the *control group other reason*. After the matching procedures, we combined the two PSM samples (i.e., mass-layoffs/plant closures vs. other reason) into one sample that we analyzed analogously to the full sample using the unconditional LCS model (see Figure 2).

Matching Procedure. A crucial step for PSM is the selection of the covariates used to estimate the propensity scores. We only used covariates in the propensity score model that were measured at M1 (i.e., before the event group entered unemployment) and selected the variables based on theoretical considerations (see Materials S1 in supplementary files). The identified covariates were included in a logistic regression model with linear effects to compute the propensity scores. To account for missing data in the covariates, we used the missing indicator plus constant method (Cham & West, 2016). Separately for (a) jobseekers from mass-layoffs or plant closures and (b) individuals who registered as jobseekers due to other reasons, we matched individuals 1:1 based on the propensity scores with nearest neighbor matching without replacement using the R package MatchIt (version 4.3.0; Ho et al., 2011). We did not impose a caliper and matched all individuals of the event groups with propensity scores within the region of common support.

Matching Jobseekers Who Registered Due to Mass-Layoffs or Plant Closures. For individuals from mass-layoffs or plant closures, the matching procedure yielded a sample of 89 matched individuals in each group. In the PSM sample, the SMD of almost all variables measured at M1 were between -0.25 and 0.25 (see Figure S1) indicating good balance between the event and control group. Only the variables *striving for perfection* (SMD = 0.26) and *job satisfaction* (SMD = -0.25) were slightly outside these thresholds. The variance ratios of almost all variables were between 0.5 and 2 (see Figure S3), which we deemed satisfactory (Stuart, 2010; Stuart & Rubin, 2008). Only the variance ratio of the expectation to "retire within the next six months" (variance ratio = 0.41) was outside these thresholds, which can be explained by the low number of individuals that expected to retire in both samples.

Matching Jobseekers Who Registered Due to Other Reasons. For individuals who registered as jobseekers due to reasons other than mass-layoffs or plant closures, the initial covariate balance after the matching procedure was not satisfactory. In order to improve the covariate balance, we imposed a caliper of one standard deviation of the propensity scores during the matching procedure. Moreover, we iteratively added those variables with the highest SMDs (i.e., *reflective coping*, *perceived stress*, *openness to new experience*) to the propensity score model until the covariate balance was satisfactory. The final matched sample consisted of 78 individuals in each group and the SMDs and variance ratios of all variables measured at M1 had acceptable values according to the previously stated thresholds (see Figures S3 and S4) indicating good balance between the event and control group (Stuart, 2010; Stuart & Rubin, 2008).

Computational Procedure

We fitted all models using the structural equation modeling software lavaan (version 0.6-9; Rosseel, 2012) in R (version 4.1.1; R Core Team, 2017) and used the robust maximum likelihood (MLR) estimator in order to account for the non-normal distribution of the indicators.[4] Full information maximum likelihood estimation was used to utilize all available information and to handle missing data (Graham & Coffman, 2012).

Analysis II: Short-Term Adaptation to Unemployment

To investigate whether the effects of unemployment change within the first months of unemployment, we used a mixed-effects trait-state-occasion model (ME-TSO; Castro-Alvarez, Tendeiro, de Jonge, et al., 2021). The ME-TSO model is rooted in latent-state-trait theory (Steyer et al., 1992, 1999, 2015), which decomposes an observed well-being variable on an occasion of measurement into three parts. First, a latent trait variable representing individual differences across situations. Second, a latent occasion-specific state residual variable representing the influence of situations as well as the interactions between persons and situations. Third, an error variable capturing the measurement error of an observation. The ME-TSO model allows to include autoregressive effects on the level of the occasion-specific state residual variables (Eid et al., 2017) and is formulated as a multilevel structural equation model, which makes it feasible to include many measurement occasions with rather short time lags (Castro-Alvarez, Tendeiro, de Jonge, et al., 2021; Castro-Alvarez, Tendeiro,

[4] We also ran the analyses based on the full sample for all categorical well-being indicators with the DWLS estimator in lavaan, which models the responses as categorical. The statistical inference was identical to the MLR estimator. Because the MLR estimator allows to interpret the results in terms of POMP scores, we only report the MLR results.

Meijer, et al., 2021). The occasion-specific state residuals and the measurement error variables are modeled on the within-person level, whereas the trait variables are modeled on the between-person level (see Figure 3 for a path diagram).

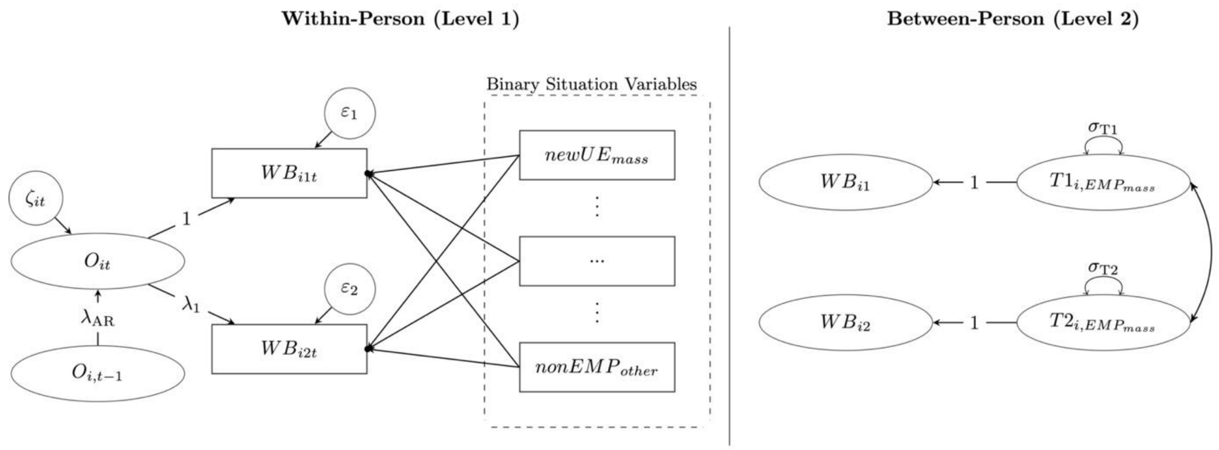
The central feature of the ME-TSO model is that it allows investigating how individual's trait levels (e.g., well-being) change between different fixed situations (Castro-Alvarez, Tendeiro, de Jonge, et al., 2021; Geiser et al., 2015). Fixed situations (in contrast to random situations) are situations that are known to the researchers, for example because they are experimentally manipulated (Geiser et al., 2015). For the present study, we defined the current employment status of an individual as the fixed situation of interest and examined how the trait well-being levels differ when individuals were unemployed for different durations compared to when they were employed. In particular, we defined the following eight employment situations in which an individual could be in at a given time: *employed*, *first month of unemployment*, *second month of unemployment*, *third month of unemployment*, *fourth month of unemployment*, *unemployed for more than four months*, *participating in an ALMP*, *having another non-employment (e.g., early retirement)*. Moreover, we differentiated between individuals who registered as jobseekers due to mass-layoffs or plant closures and individuals who registered due to other reasons. This way, each individual could be in one of 16 situations at a given time (eight employment situations x two reasons for job seeking registration). We selected the situation *being employed and having registered as a jobseeker due to mass-layoffs or plant closures* as the reference situation and defined 15 dummy variables to model the other (non-reference) situations (see Table S10 for coding scheme). By regressing the well-being indicators at a given time onto these 15 dummy variables, we modeled the trait changes between a given employment situation (e.g., *newly unemployed and job seeking due to mass-layoffs or plant closures)* and the reference situation (*being employed and job seeking due to mass-layoffs or plant closures*). Specifically, the regression coefficients of the binary situation variables correspond to the differences in the trait levels between being in the specific employment situation and being in the reference situation. Given that there is only one occasion of measurement for an individual for the fixed situations "first month of unemployment", "second month of unemployment", and "third month of unemployment" the parameters of the dummy variables were defined as fixed effects (and not random effects). Therefore, parameters of the dummy variables represent general fixed effects such as in traditional regression analysis with dummy variables. Importantly, all effects were calculated separately for each indicator (i.e., item) of a given well-being facet. Moreover, the (indicator-specific) trait levels during the reference situation were modeled as random variables at the between-person level. For single-item well-being indicators (i.e., the domain satisfaction items and *psychological growth*) we used a structurally analogous model and specified the autoregressive effects on the level of the observed variables.

Sample

The analyses based on the ME-TSO model were based on all individuals of the GJSP (N = 1540). However, as no missing values on the dummy situation variables are permitted in the ME-TSO model, we discarded observations for each individual after the first missing value on the employment status variable (i.e., right censoring). Moreover, to model the well-being changes adequately, we only included individuals with at least three observations on the outcome variables. This way, the final samples sizes varied between 1,000 (e.g., *satisfaction with household income*) and 1,139 individuals (*satisfaction with life*) with an average number of 15.4 to 16.8 measurement occasions.

Figure 3

Exemplary ME-TSO Model with Two Indicators



Note. WB_{i1t} and WB_{i2t} are observed well-being scores of person *i* at time *t*. ε_1 and ε_2 are residual variances of these well-being indicators. O_{it} is the occasion-specific residual variable with a residual variance of ζ_{it}. λ_{AR} is the autoregressive effect of O_{it-1} on O_{it}. The factor loading of the first well-being indicator on O_{it} is set to 1 in order to identify the model, the factor loadings of the other well-being indicators are freely estimated. The regression coefficients of the binary situation variables (i.e., dummy variables) on the well-being indicators are fixed across individuals. Latent trait variables are modeled as random variables on the between-person level (i.e., $T1_{i,EMP,mass}$, $T2_{i,EMP,mass}$) with a variance of σ_{T1} and σ_{T2} (see Castro-Alvarez, Tendeiro, de Jonge, et al., 2021; Geiser et al., 2015).

Computational Procedure

For each of the 18 well-being facets, we ran separate ME-TSO models. All models were fitted with the commercial software Mplus (version 8.7; Muthén & Muthén, 2017) using the dynamic structural equation modeling framework (DSEM; Asparouhov et al., 2017, 2018). DSEM relies on the Bayesian estimation procedure implemented in MPlus (Asparouhov & Muthén, 2010). We used the default uninformative priors for all parameters and estimated the models using two Monte Carlo chains, each running for at least 400,000 iterations. We defined a seed for the Monte Carlo process to ensure reproducibility of the results. The posterior distribution of each parameter was based on every 20th iteration (i.e., thinning) of the second half of each chain (i.e., after the burn-in period). Thus, the parameter estimates were based on at least 20,000 posterior draws. In order to ensure convergence of the Monte Carlo chains, we further set the Mplus convergence criterion, which relates to the potential scale reduction (PSR) factor, to a stricter value (bconvergence = 0.025) compared to the Mplus default (bconvergence = 0.05). In addition, we visually checked the Bayesian posterior parameter trace plots and the Bayesian autocorrelation plots for several randomly chosen models. We obtained point estimates for the parameters by using the median of the posterior distribution and used the posterior quantiles to derive 95% credibility intervals for each estimate. We imported the Mplus model results to R (version 4.1.1; R Core Team, 2017) using the R-package MplusAutomation (version 1.0.0; Hallquist & Wiley, 2018).

Summary Analysis Strategy

In sum, the analyses based on the LCS models allow deriving highly controlled between-person effects (i.e., event vs. control group) of entering unemployment using a causal modeling framework. However, the research design is minimalistic and only relies on two measurement occasions. To examine if staying unemployed for longer time periods affects the well-being facets beyond the immediate effect occurring within the first month of unemployment, we conducted the second set on analyses based on the ME-TSO model. These analyses are, however, limited in terms of the causal inferences that they permit. Taken together, the two analysis strategies provide a detailed picture of unemployment-related well-being changes in proximity to a job-loss.

Transparency and Openness

This study's design and its analyses were not preregistered. Analysis scripts and full model results are available at https://osf.io/jfms4. The data is available for researchers upon request.

Results

Descriptive Results

Table S1 depicts descriptive statistics on (a) the full GJSP sample, (b) the full sample of the LCS analyses and (c) the matched sample of the LCS analyses separately for individuals who registered as jobseekers due to mass-layoffs or plant closures and individuals who registered as job seeking due to a different reason. Moreover, Tables S2-S5 in the supplementary materials provide a detailed overview of the means, standard deviations and available sample sizes for the well-being indicators across the first two measurement waves of the GJSP (i.e., M1 and M2).

Analysis I: Immediate Effects of Unemployment

Tables S6 and S7 in the supplementary materials depict the item reliabilities for the multi-item well-being facets based on the strong MI models used to investigate measurement invariance. Moreover, they present the aggregated scale reliabilities, consistencies, indicator-specificities (for computations see Eid et al., 2003, p. 59) as well as the (latent) correlations between M1 and M2.

Measurement Invariance

Model fit indices of the latent state models with configural and strong MI for all multi-item well-being facets based on the full LCS sample are depicted in Table S8 in the supplementary materials. The configural MI models for *happy*, *awake* and *experienced meaning* yielded negative residual variances. Moreover, the strong MI model for *happy* yielded negative residual variances, thus we restricted the error variances to be equal over time and across items for the *happy* model (i.e., strict MI). Most models with strong MI showed good fit according to the χ^2 - values, the rmsea and a non-significant likelihood ratio test as well as a smaller BIC value when compared to the respective configural MI model. The strong MI models for the scales *awake* and *environmental mastery* as well as the strict MI model for *happy* had a significant *p*-value indicating misfit. However, the likelihood ratio test for the models of *environmental mastery* indicated that the strong MI model does not significantly reduce the χ^2 - value compared to the configural MI model (p = .23).

Moreover, the BIC of the strong MI model for *environmental mastery* was smaller than the BIC of the configural model suggesting that the strong MI model is justified. Thus, the assumption of strong MI across M1 and M2 seems to hold for all multi-item measures of well-being except for *happy* and *awake*. We will still present the model results for these two well-being facets in the following; however, readers should be cautious when interpreting the coefficients of these models. The propensity-score matched sample yielded similar results (see Table S9 in the supplementary materials).

Differences in Intraindividual Change

In the following, we focus on the immediate effects derived from the LCS models based on the full sample and compare them to the results obtained from the two robustness checks. Table 1 depicts the DiD estimates that represent these immediate effects for the three sets of LCS analyses. Additional results based on the LCS models for on the full sample (e.g., average pre-event differences between the groups) are presented in Table S11 in the supplementary materials. The full results for all LCS models can be found in the online repository of this study (https://osf.io/jfms4). Running separate LCS models for both groups of jobseekers yielded nearly identical results (see Table S12 in the supplementary materials).

Cognitive Well-being. The estimated immediate effect of entering unemployment on *life satisfaction* for individuals who lost their job due to mass-layoffs or plant closures is -4.74 p.p. (z = -2.52, p = .012). Moreover, entering unemployment had a statistically significant immediate effect on the *satisfaction with household income* for these individuals of -7.78 p.p. (z = -2.59, p = .01), whereas the effects of entering unemployment on the satisfaction with *family life*, *household activities* and *leisure* were not significantly different from zero. The two robustness checks yielded highly similar results.

Table 1

Immediate Effects of Unemployment for Different Reasons for the Job Seeking Registration

Well-being Facet	Mass-Layoff or Plant Closure				Other Reason			
	LCS (Full Sample)	LCS with Covariates (Full Sample)	LCS (PSM Sample)	ME-TSO	LCS (Full Sample)	LCS with Covariates (Full Sample)	LCS (PSM Sample)	ME-TSO
ls	**-4.74** [-8.42;-1.06] ($p = .012$)	**-5.33** [-9.01;-1.65] ($p = .004$)	**-6.07** [-10.07;-2.08] ($p = .003$)	**-4.48** [-6.12;-2.83] ($p < .001$)	-2.35 [-5.68;0.97] ($p = .165$)	-3.42 [-7.33;0.48] ($p = .086$)	-2.07 [-6.99;2.85] ($p = .409$)	-3.52 [-8.09;0.82] ($p = .116$)
fSat	-0.63 [-5.65;4.39] ($p = .804$)	-1.92 [-7.1;3.27] ($p = .468$)	0.1 [-5.53;5.73] ($p = .972$)	1.28 [-0.77;3.3] ($p = .216$)	0.23 [-4.02;4.48] ($p = .914$)	-2.01 [-7;2.98] ($p = .429$)	1.33 [-5.3;7.97] ($p = .694$)	-1.92 [-5.85;2.06] ($p = .344$)
hSat	3.86 [-1.35;9.07] ($p = .147$)	2.98 [-2.57;8.53] ($p = .292$)	1.07 [-4.53;6.66] ($p = .709$)	0.21 [-1.81;2.25] ($p = .836$)	1.12 [-3.65;5.9] ($p = .644$)	-0.61 [-6.04;4.82] ($p = .826$)	-0.93 [-7.69;5.84] ($p = .789$)	-0.33 [-4.02;3.3] ($p = .852$)
iSat	**-7.78** [-13.66;-1.89] ($p = .01$)	**-9.59** [-15.37;-3.8] ($p = .001$)	**-10.07** [-15.4;-4.74] ($p < .001$)	**-7.25** [-9.13;-5.36] ($p < .001$)	**-5.74** [-10.07;-1.42] ($p = .009$)	**-8.37** [-13.11;-3.62] ($p < .001$)	**-5.99** [-11.16;-0.83] ($p = .023$)	**-8.62** [-11.87;-5.31] ($p < .001$)
lSat	2.78 [-3.09;8.65] ($p = .353$)	1.55 [-4.46;7.56] ($p = .613$)	1.31 [-5.18;7.8] ($p = .692$)	**5.02** [2.77;7.27] ($p < .001$)	**5.3** [0.48;10.12] ($p = .031$)	2.78 [-2.79;8.34] ($p = .328$)	4.49 [-2.92;11.9] ($p = .235$)	2.32 [-1.38;5.99] ($p = .22$)
happy	-1.78 [-6.73;3.16] ($p = .48$)	-2.55 [-7.59;2.5] ($p = .322$)	-2.74 [-7.99;2.51] ($p = .306$)	1.75 [-0.48;4.02] ($p = .124$)	**-4.36** [-8.53;-0.19] ($p = .04$)	**-6.24** [-10.66;-1.83] ($p = .006$)	-4.55 [-10.33;1.23] ($p = .123$)	-0.14 [-4.28;4.05] ($p = .942$)
awake	1.07 [-3.94;6.09] ($p = .675$)	0.4 [-4.9;5.7] ($p = .882$)	3.38 [-2.19;8.95] ($p = .235$)	**2.46** [0.22;4.73] ($p = .032$)	2.26 [-1.63;6.15] ($p = .255$)	0.87 [-3.48;5.22] ($p = .695$)	3.93 [-1.87;9.73] ($p = .184$)	**-4.7** [-8.8;-0.31] ($p = .038$)
calm	-2.8 [-8.01;2.42] ($p = .293$)	-3.13 [-8.46;2.19] ($p = .249$)	-3.01 [-8.77;2.75] ($p = .306$)	-0.56 [-2.84;1.66] ($p = .618$)	-1.05 [-5.08;2.98] ($p = .61$)	-1.59 [-6.09;2.9] ($p = .487$)	3.48 [-2.74;9.71] ($p = .273$)	-2.9 [-7.18;1.29] ($p = .172$)
good	-5.09 [-11.7;1.53] ($p = .132$)	-6.74 [-13.52;0.04] ($p = .051$)	-4.92 [-12.3;2.46] ($p = .191$)	-0.82 [-3.81;2.27] ($p = .606$)	-0.75 [-6.13;4.63] ($p = .785$)	-3.6 [-9.57;2.38] ($p = .238$)	-5.11 [-12.74;2.52] ($p = .189$)	-0.39 [-6.07;5.46] ($p = .898$)
worry	0.92 [-5.54;7.39] ($p = .78$)	0.15 [-6.46;6.76] ($p = .965$)	-1.85 [-10.09;6.38] ($p = .659$)	0 [-3.1;3.08] ($p = .998$)	3.49 [-2.05;9.03] ($p = .217$)	2.67 [-3.33;8.66] ($p = .383$)	2.1 [-5.31;9.51] ($p = .578$)	-2.02 [-7.15;2.97] ($p = .434$)
sad	2.99 [-3.39;9.36] ($p = .358$)	3.42 [-2.96;9.79] ($p = .293$)	3.77 [-3.27;10.81] ($p = .293$)	0.36 [-2.6;3.34] ($p = .806$)	1.18 [-4.52;6.88] ($p = .686$)	1.9 [-4.54;8.33] ($p = .563$)	2.21 [-6.12;10.55] ($p = .602$)	2.18 [-3.24;7.72] ($p = .434$)
accept	0.28 [-2.99;3.56] ($p = .865$)	0.51 [-2.78;3.81] ($p = .76$)	0.46 [-3.31;4.22] ($p = .812$)	-0.21 [-2.06;1.64] ($p = .822$)	-1.24 [-4.01;1.53] ($p = .379$)	-1.18 [-4.2;1.84] ($p = .444$)	-1.73 [-5.48;2.03] ($p = .368$)	-3.9 [-8.33;0.6] ($p = .088$)
mastery	-0.18 [-4.96;4.59] ($p = .94$)	-0.07 [-5.01;4.88] ($p = .979$)	0.22 [-5.31;5.74] ($p = .938$)	-0.64 [-2.84;1.56] ($p = .566$)	-1.88 [-6.4;2.65] ($p = .416$)	-2.02 [-6.86;2.83] ($p = .415$)	1.13 [-4.81;7.07] ($p = .709$)	-3.92 [-9.06;1.36] ($p = .142$)
posRel	-2.93 [-7.58;1.72] ($p = .217$)	-2.25 [-7.03;2.53] ($p = .356$)	-4.72 [-9.88;0.44] ($p = .073$)	-0.24 [-2.32;1.87] ($p = .826$)	-1.9 [-5.82;2.02] ($p = .342$)	-1.08 [-5.52;3.37] ($p = .635$)	-0.37 [-6.47;5.74] ($p = .907$)	1.25 [-4.89;7.3] ($p = .69$)
purp	-0.13 [-5.19;4.93] ($p = .96$)	0.07 [-5.12;5.25] ($p = .98$)	-0.06 [-5.67;5.55] ($p = .983$)	1.65 [-0.42;3.78] ($p = .12$)	-3.67 [-7.53;0.19] ($p = .063$)	-3.24 [-7.51;1.02] ($p = .136$)	0.55 [-4.81;5.9] ($p = .841$)	-4.28 [-9.5;0.89] ($p = .104$)
auto	0.74 [-3.81;5.29] ($p = .751$)	0.79 [-3.77;5.34] ($p = .736$)	0.56 [-5.54;6.66] ($p = .857$)	-1.52 [-3.69;0.7] ($p = .174$)	0 [-3.35;3.35] ($p = 1$)	-0.02 [-3.67;3.63] ($p = .99$)	-0.81 [-6.34;4.73] ($p = .775$)	-1.02 [-5.69;3.59] ($p = .656$)
growth	1.63 [-2;5.26] ($p = .378$)	0.83 [-2.85;4.51] ($p = .659$)	-0.56 [-4.62;3.51] ($p = .789$)	**3.42** [1.7;5.17] ($p < .001$)	2.33 [-0.69;5.35] ($p = .131$)	0.92 [-2.5;4.35] ($p = .597$)	0.93 [-4.03;5.88] ($p = .714$)	**4.82** [1.11;8.57] ($p = .01$)
meaning	2.3 [-3.5;8.11] ($p = .437$)	3.03 [-3.06;9.12] ($p = .33$)	0.17 [-6.44;6.77] ($p = .96$)	-0.46 [-3.35;2.46] ($p = .756$)	-0.77 [-6.27;4.72] ($p = .783$)	-0.95 [-7.19;5.29] ($p = .766$)	-2.03 [-9.67;5.62] ($p = .604$)	0.77 [-4.48;6.05] ($p = .772$)

Note. LCS = latent change score models; PSM = propensity score matched; ME-TSO = mixed-effects trait-state-occasion model; 95%-confidence or credible intervals are presented in brackets, and the two-sided p-values in parentheses. When coefficients are printed in bold, their confidence or credibility intervals do not contain zero. The parameters of the ME-TSO model for the "other reason" group were computed based on the parameters of the situational dummy variables (for formulas see Mplus Outputs in the online repository of this study: https://osf.io/jfms4). We used the following abbreviations for the well-being facets: ls: *life satisfaction*; hSat: *satisfaction with household activities*; iSat: *satisfaction with household income*; lSat: *satisfaction with leisure*; fSat: *satisfaction with family life*; happy: *momentary mood: happy*; awake: *momentary mood: awake*; calm: *momentary mood: calm*; worry: *worried mood (in last week)*; sad: *sad mood (in last week)*; good: *good mood (in last week)*; accept: *self-acceptance*; mastery: *environmental mastery*; posRel: *positive relations with* others; purp: *sense of purpose*; auto: *autonomy*; growth: *psychological* growth; meaning: *experienced meaning (ESM).*

For individuals who lost their jobs due to reasons other than mass-layoffs or plant closures, the immediate effects on *life satisfaction* (*DiD* = -2.35, *z* = -1.39, *p* = .17) and *satisfaction with household income* (*DiD* = -5.74, *z* = -2.60, *p* = .01) were smaller (and not statistically different from zero in the case of *life satisfaction*). The estimated immediate effect of entering unemployment on one's *leisure satisfaction* was positive and statistically different from zero for these individuals (*DiD* = 5.30, *z* = -2.16, *p* = .03). However, this effect was not statistically different from zero in the two robustness checks. The immediate effects of unemployment on the *satisfaction with one's family life* or *one's household activities* were not statistically different from zero for these individuals.

Affective Well-being. For individuals who lost their jobs due to mass-layoffs or plant closures, the estimated immediate effects of unemployment on the examined AWB facets ranged from -5.09 p.p. (*good mood in last week*) to 2.99 p.p. (*sad mood in last week*), with none of the effects being statistically significant. The two robustness analyses yielded highly similar results. For individuals who lost their jobs due to a different reason, the immediate effects of entering unemployment on the AWB facets ranged from -4.36 (*happy*) to 3.49 (*worried mood within last week*) with only the effect on *happy* being statistically different from zero (*z* = -2.13, *p* = .04). However, this effect was non-significant in the PSM sample.

Eudaimonic Well-being. For individuals who lost their jobs due to mass-layoffs or plant closures, the estimated immediate effects of unemployment on the facets of the Ryff-Scale ranged from -2.93 p.p. (*positive relations with others)* to 1.63 p.p. (*psychological growth*). The immediate effect on *momentarily experienced meaning* was 2.30 p.p.. However, none of the effects were statistically significant. The two robustness checks yielded highly similar results. For individuals who lost their jobs due to other reasons, the immediate effects of unemployment on the facets of the Ryff-Scale ranged from -3.67 (*purpose in life*) to 2.33 (*psychological growth*) and the estimated effect on *momentarily experienced meaning* was -0.77, again, all these effects were not statistically different from zero.

Analysis II: Short-Term Adaptation to Unemployment

All ME-TSO models converged based on the Mplus convergence criterion and our visual inspection of the Markov chains. The online repository (https://osf.io/jfms4) contains all Mplus output files. Table 1 depicts the average immediate (within-person) effects of entering unemployment (i.e., comparing the average well-being levels within the first month of unemployment to all periods of employment of a given individual) for the reference indicator separately for individuals who (a) registered as jobseekers due to mass-layoffs and plant closures and (b) for subjects who registered due to a different reason. Figures 4 – 6 illustrate the model-implied average well-being levels in terms of the reference indicators for different unemployment durations and compare these levels to the model-implied average well-being level during employment. In all analyses, we deemed effects as statistically significant if the 95%-credibility interval did not contain zero. Moreover, Figures 4 – 6 indicate whether the effects of being unemployed for more than one month differed from the immediate effects of entering unemployment based on the ME-TSO model.

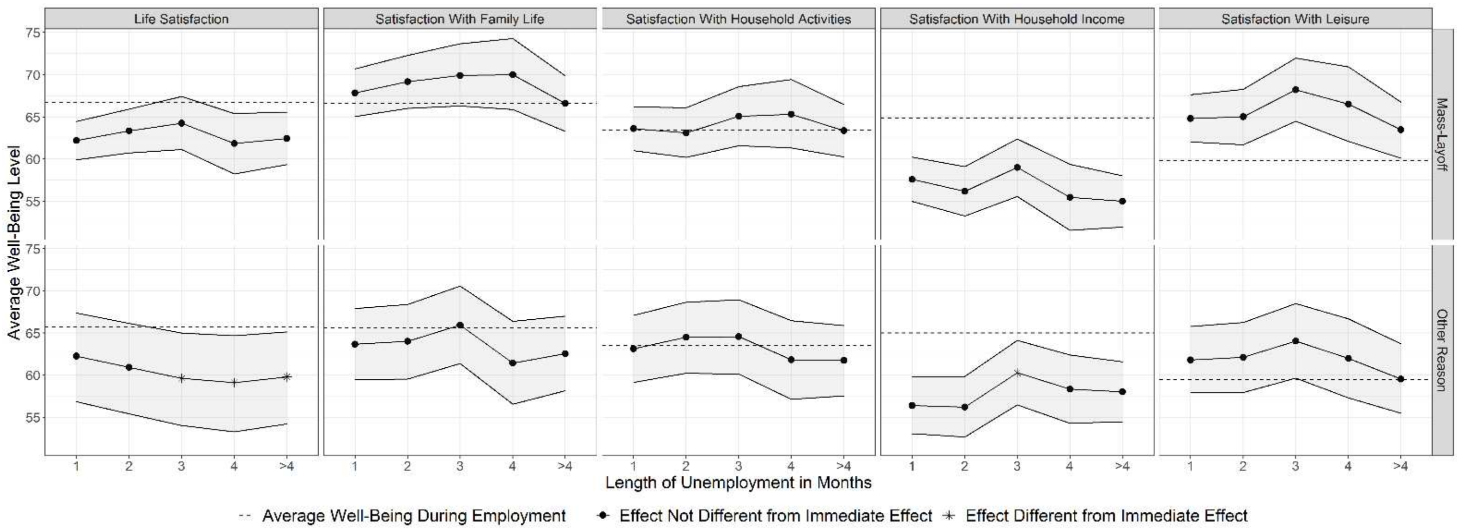
Cognitive Well-being

For individuals from companies conducting mass-layoffs or plant closures, average levels of *life satisfaction* (-4.48 p.p.) and *income satisfaction* (-7.25 p.p.) were significantly lower during the first month of unemployment compared to being employed, whereas average levels of *leisure satisfaction* (5.02 p.p.) were significantly higher. The immediate effects of unemployment on *family satisfaction* and *satisfaction with the household activities* were not statistically different from zero in the ME-TSO analyses for these individuals. Moreover, the effects of being unemployed for more than one month did not significantly differ from the immediate effects (i.e., no adaptation).

For individuals who registered as jobseekers due to reasons other than mass-layoffs or plant closures, entering unemployment had an immediate negative effect on the *satisfaction with one's household income* (-8.62 p.p.) in the ME-TSO model. The average levels of the other examined CWB facets did not significantly differ between the first month of unemployment and all periods of employment. However, *life satisfaction* levels were significantly lower when these individuals were unemployed for more than three months, which indicates adaptation. Moreover, in the third month of unemployment, the estimated effect on the *satisfaction with one's household income* was significantly different from the respective immediate effect of entering unemployment (i.e., smaller negative effect). The other effects of being unemployed for longer than one month did not significantly differ from the respective immediate effects.

Figure 4

Average Levels of the Examined Cognitive Well-Being Facets for Different Lengths of Unemployment



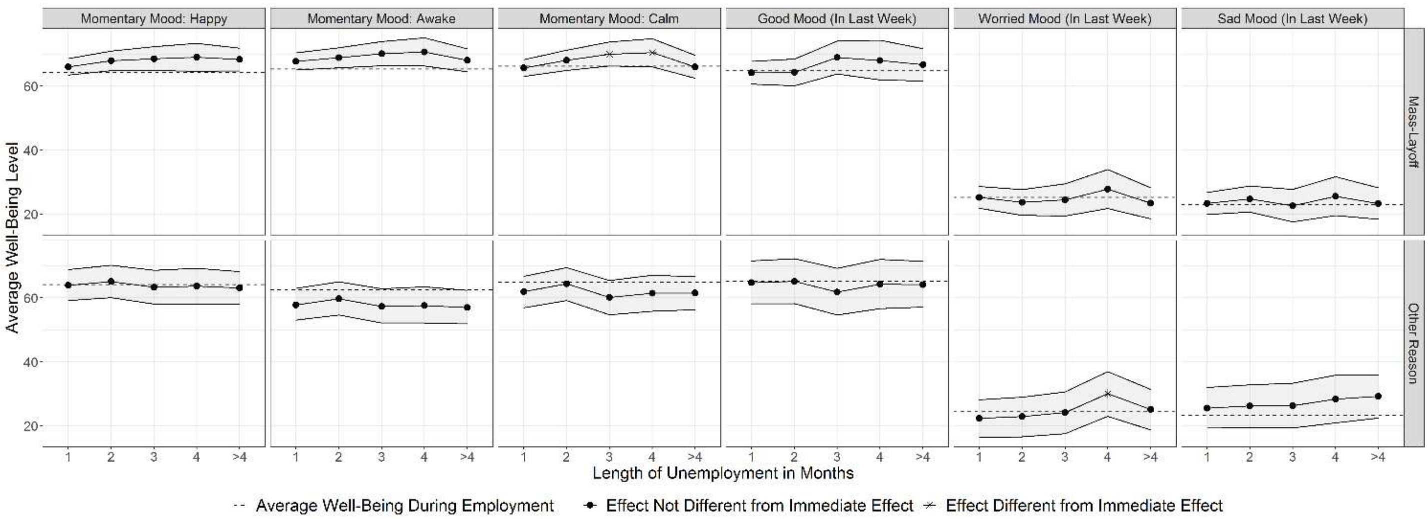
Note. The plot depicts the model-implied well-being levels of the reference indicator for varying lengths of unemployment based on the ME-TSO models. The values were computed based on the parameters of the situational dummy variables and item intercepts (for formulas see Mplus Outputs in the online repository of this study: https://osf.io/jfms4). The grid columns refer to the various well-being facets and the grid rows to the reason for the job seeking registration. The confidence bands correspond to the 95%-credibility intervals, the dashed line depicts the model-implied well-being levels during employment. The estimated immediate effects correspond to the difference between the dashed line and the first data point on the left of each plot. Effects of prolonged unemployment that are statistically different from the immediate effects are depicted using stars.

Affective Well-being

Individuals from mass-layoffs or plant closures were on average significantly more *awake* (2.46 p.p.) within the first month of unemployment compared to when they were employed. The immediate effects of unemployment on the other examined AWB facets were not statistically different from zero. In the third and fourth month of unemployment, the estimated effect on *calm* was significantly different from the immediate effect of entering unemployment (i.e., greater positive effect). For the other AWB facets, the effects of being unemployed for longer than one month did not significantly differ from the immediate effects.

Figure 5

Average Levels of the Examined Affective Well-Being Facets for Different Lengths of Unemployment



Note. The plot depicts the model-implied well-being levels of the reference indicator for varying lengths of unemployment based on the ME-TSO models. The values were computed based on the parameters of the situational dummy variables and item intercepts (for formulas see Mplus Outputs in the online repository of this study: https://osf.io/jfms4). The grid columns refer to the various well-being facets and the grid rows to the reason for the job seeking registration. The confidence bands correspond to the 95%-credibility intervals, the dashed line depicts the model-implied well-being levels during employment. The estimated immediate effects correspond to the difference between the dashed line and the first data point on the left of each plot. Effects of prolonged unemployment that are statistically different from the immediate effects are depicted using stars.

Individuals who registered as jobseekers due to reasons other than mass-layoffs or plant closures were on average significantly less *awake* (4.7 p.p.) during the first month of unemployment compared to when they were employed. The levels of the other facets of AWB did not significantly differ between the first month of unemployment and periods of employment. However, the effect of being unemployed for four months on *worried mood within the last week* was significantly different from the immediate effect of entering unemployment (i.e., greater positive effect). The other effects of being unemployed for longer than one month did not significantly differ from the immediate effects for these individuals.

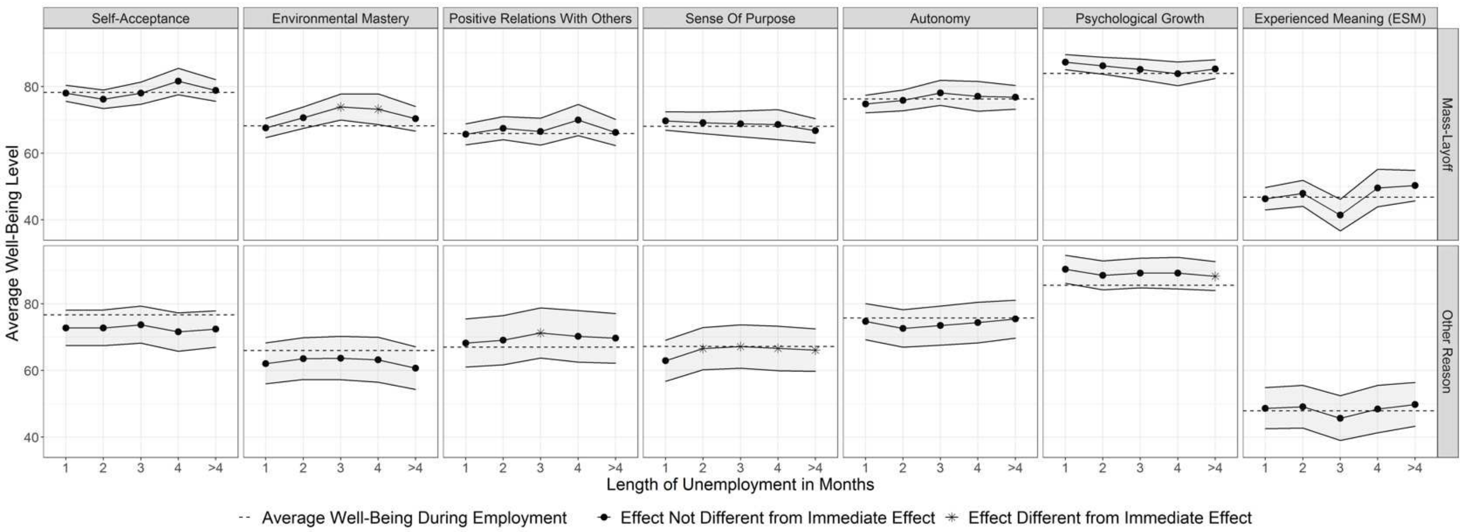
Eudaimonic Well-being

Based on the ME-TSO model, individuals from mass-layoffs or plant closures reported on average significantly higher values on *psychological growth* (3.42 p.p.) during the first month of unemployment compared to periods when they were employed. The immediate effects of unemployment on the other examined EWB facets were not statistically different from zero for these individuals. In the third and fourth month of unemployment, the estimated effect on *environmental mastery* was significantly different from the immediate effect of entering unemployment (i.e., greater positive effect). For the other examined EWB facets, the effects of being unemployed for longer than one month did not significantly differ from the respective immediate effects.

Individuals who registered as jobseekers due to reasons other than mass-layoffs or plant closures reported on average significantly higher levels on *psychological growth* (4.82 p.p.) during the first month of unemployment compared to when they were employed. The levels of the other examined EWB facets did not significantly differ between the first month of unemployment and periods of employment. However, the effect of being unemployed for more than four months on *psychological growth* and the effect of being unemployed for three months on *positive relations with others* were significantly different from the respective immediate effects of entering unemployment. Moreover, the effect of being unemployed for more than two months on *sense of purpose* was significantly different from the immediate effect of entering unemployment (i.e., smaller negative effect). The other effects of being unemployed for longer than one month did not significantly differ from the respective immediate effects.

Figure 6

Average Levels of the Examined Eudaimonic Well-Being Facets for Different Lengths of Unemployment



Note. The plot depicts the model-implied well-being levels of the reference indicator for varying lengths of unemployment based on the ME-TSO models. The values were computed based on the parameters of the situational dummy variables and item intercepts (for formulas see Mplus Outputs in the online repository of this study: https://osf.io/jfms4). The grid columns refer to the various well-being facets and the grid rows to the reason for the job seeking registration. The confidence bands correspond to the 95%-credibility intervals, the dashed line depicts the model-implied well-being levels during employment. The estimated immediate effects correspond to the difference between the dashed line and the first data point on the left of each plot. Effects of prolonged unemployment that are statistically different from the immediate effects are depicted using stars. ESM = experience sampling method.

Discussion

This study investigated how unemployment affects cognitive, affective and eudaimonic well-being facets in proximity to a job-loss based on novel monthly panel data of initially employed German jobseekers who are at high risk of losing their job. The first set of analyses provide highly controlled insights into how the various well-being facets changed from the last month in employment to the first month in unemployment. Specifically, these analyses allow isolating the immediate effects of entering unemployment from anticipatory effects occurring before the job-loss. The second set of analyses provide researchers and practitioners with a nuanced picture of the well-being dynamics within the first months of unemployment and examine patterns of short-term adaptation. In the following, we will summarize and integrate the main findings of both analyses and discuss the implications of the results.

Immediate Effects of Unemployment

We examined how the various well-being facets changed from the last month in employment to the first month in unemployment using latent change score (LCS) models. By accounting for general well-being changes occurring in a control group of continuously employed individuals, we aimed at addressing important threats to internal validity in order to obtain effect estimates that are as similar as possible to causal effect estimates in the current context. To strengthen the internal validity further, we focused on jobseekers from companies conducting mass-layoffs or plant closures in the causal analyses. We checked the robustness of the results as well as the validity of the model assumptions in two ways. First, we included the employment-related expectations measured at the first measurement occasion as control variables in the model. Second, we re-ran the analyses using a propensity score matched subsample, in which all observed covariates were balanced between the event and control groups at the first measurement occasion (i.e., one month before the event group entered unemployment). All three sets of LCS analyses yielded highly similar inferences suggesting that the analyses are robust and the main assumptions are valid. In the discussion below, we will focus on the results of the unconditional LCS models based on the full sample.

Cognitive Well-Being

For jobseekers from companies conducting mass-layoffs or plant closures, becoming unemployed had an average immediate effect on life satisfaction of 4.74 p.p.. This finding indicates that the actual transition into unemployment had an immediate negative effect on life satisfaction that went beyond any anticipatory effects occurring in the months before the job-loss. For individuals who registered as jobseekers due to reasons other than mass-layoffs or plant closures, the immediate effect of entering unemployment on life satisfaction was smaller and not statistically significant. This finding might be explained by the fact that the majority of these individuals 'lost' their jobs due to expiring contracts and thus (a) had more time to anticipate the job-loss and (b) were better able to prepare themselves for the transition into unemployment. Moreover, some of these individuals likely also had the opportunity to prolong their contract but voluntarily decided not to. As a result, they might experience the transition into unemployment less negative.

In order to interpret the magnitude of the immediate effects of entering unemployment on life satisfaction, it is helpful to compare them to the effects found in studies based on representative German panel data from the SOEP. Luhmann et al. (2014), for example, reported that life satisfaction dropped by 4.1 p.p. from the year prior to unemployment to the first year in unemployment when controlling for household income. Gebel and Voßemer (2014) found that life satisfaction decreased by 7.8 p.p. from the last year in employment to the first year being unemployed using a difference-in-difference approach combined with propensity score matching, which closely resembles our analytic approach. Kassenboehmer and Haisken-DeNew (2009) reported similar effects of unemployment on life satisfaction for Germans that lost their jobs due to company closures. Using ordinary-least-squares fixed effects regression with several control variables, they found that unemployment reduced life satisfaction by roughly 6.5 p.p. for men and 3.5 p.p. for women.

In addition, the effects can be compared to international panel studies. Yap et al. (2012), for instance, used British data and a nonlinear regression model with a control group to investigate how becoming unemployed changes life satisfaction. They reported that life satisfaction dropped by 0.35 points on a 7-point scale (i.e., 5 p.p.) more within one year for individuals that entered unemployment compared to an employed control group. Analyses based on the same nonlinear regression model with a control group indicated that unemployment decreased life satisfaction by 4 p.p. in Swiss data (Anusic et al., 2014b) and 1.2 p.p. in Australian data (Anusic et al., 2014a). Thus, the overall magnitude of the yearly-effects based on representative panel data are highly similar to the immediate month-to-month effects of the present study for individuals from mass-layoffs or plant closures. The similarity of these results suggest that the actual transition into unemployment (and not the anticipation of unemployment) seems to be the central driver of the observed changes in life satisfaction.

In addition, the present study indicates that entering unemployment has a negative immediate effect on the satisfaction with the household income regardless of the reason for the job-loss. The estimated effects are -7.78 p.p. (mass-layoff or plant closure) and -5.74 p.p. (other reason) and thus notably smaller than the effect found by Chadi & Hetschko (2017), who reported a decrease in satisfaction with income of 16 p.p. from two years before entering unemployment to the first year in unemployment based on SOEP data. These divergent results might be explained by the fact that companies often already have to cut their employees' salaries in the months and years before they have to lay off a share of their employees. This way, individuals are likely already less satisfied with their household income before entering unemployment. Alternatively, the decline of income satisfaction observed in previous studies might be due to shattered future income *expectations* and hence largely anticipatory. In fact, the immediate income loss is buffered by unemployment benefits and other family members' earnings, while the individual's expected future incomes reduce substantially (e.g., Eliason & Storrie, 2006). Our study provides further evidence of such prospective effects for individuals from companies conducting mass-layoffs or plant closures by showing that individuals in the event group are already on average 6.5 p.p. less satisfied with their household income one month before entering unemployment compared to individuals in the control group (see Table S11).

Further, the present study indicates that entering unemployment does not have an immediate effect on the satisfaction with one's *family life* and *household activities* regardless of the reason for the job-loss. The results in terms of *leisure satisfaction* are mixed. For individuals from companies conducting mass-layoffs or plant closures, we did not find a significant effect in the LCS models but the effect in the ME-TSO model was statistically significant and predicted that individuals are on average 5 p.p. more satisfied with their leisure within the first month of unemployment compared to all employment periods. These differences are likely due to the different comparison standards in both models. The LCS model compares the well-being levels of the last month before unemployment to the first month of unemployment (while accounting for the well-being changes in the control group) whereas the ME-TSO model compares the well-being levels of the first month of unemployment to the average levels across *all* employment periods of a given person. In particular, it is likely that the satisfaction with leisure is already increased for individuals from companies conducting mass-layoffs or plant closures in the weeks and months leading up to the job-loss, as these individuals often already work less during this time. This idea is supported by the finding that individuals in the *event group mass-layoff* (i.e., who are going to become unemployed within the next month) were already significantly more satisfied with their leisure (6 p.p.) than the continuously employed *control group mass-layoff* (see Table S11 in supplementary materials). Contrarily, the immediate effects of entering unemployment on satisfaction with leisure for individuals who registered as jobseekers due to reasons other than mass-layoffs or plant closures were inconsistent across the LCS model. Thus, more research is needed to better understand the dynamics in terms of leisure satisfaction for these individuals.

Affective Well-Being

For individuals from mass-layoffs and plant closures, becoming unemployed did not have a statistically significant immediate effect on the momentarily assessed mood states *happy*, *awake* and *calm* or feeling *good*, *worried* or *sad* within the last week. The results for individuals who registered as jobseekers due to other reasons indicate that entering unemployment seems to have a significant negative immediate effect on *feeling happy* (-4.4 p.p.). However, the model results for *feeling happy* and *feeling awake* should be treated with caution as their fit statistic indices indicated misfit. The immediate effects derived from the ME-TSO model were also not statistically significant from zero, except for *feeling awake*. Individuals who registered as jobseekers due to mass-layoffs or plant closures were predicted to be on average 2.5 p.p. more awake during the first month of unemployment compared to when they were employed. Contrarily, individuals who registered as jobseekers due to other reasons, were predicted to be on average 4.7 p.p. less awake during the first month of unemployment compared to when they were employed. More research is needed to test the robustness of these result and to examine possible explanations. Overall, the general lack of immediate effects of entering unemployment on the examined AWB facets is in line with our expectations and earlier findings indicating that unemployment does not seem to affect AWB facets (e.g., Knabe et al., 2010).

Eudaimonic Well-Being

Based on the LCS models, becoming unemployed did not have an immediate effect on any of the investigated EWB facets (regardless of the examined reason for the job-loss). The facets of the Ryff-Scale were highly stable across time with latent retest correlation of about .9 over one month (see Table S6), which makes short-term changes rather unlikely. The immediate effects of unemployment based on the ME-TSO model were also mostly not statistically different from zero. The exceptions were the significant effects in terms of *psychological growth* for individuals from mass-layoffs or plant closures (3.4 p.p.) and for individuals who registered as jobseekers due to other reasons (4.8 p.p.). Again, these differences between the LCS models and the ME-TSO models likely stem from the different comparison standards and the fact that the level of *psychological growth* on the first measurement occasion was not equal to the average levels across all employment periods. Overall, the present study indicates that the examined EWB facets do not seem to be immediately affected by entering unemployment.

Short-Term Adaptation to Unemployment

To examine whether individuals adapt to being unemployed within the first months of unemployment, we used a ME-TSO model. The results of the ME-TSO analyses indicate that the well-being levels within the first months of unemployment were fairly stable. Across the examined well-being facets, we did not find meaningful and consistent patterns of short-term adaptation to unemployment. The only exception was that life satisfaction of individuals who lost their jobs due to reasons other than mass-layoffs or plant closures decreased with prolonged unemployment durations. This result suggests that for individuals who lost their jobs due to reasons other than mass-layoffs or plant closures (i.e., mostly due to expiring contracts), the negative effects of unemployment in terms of decreased life satisfaction seem to develop over time rather than immediately in the first month of unemployment.

Summary

The study underlines that becoming unemployed differentially affects well-being and shows that the reason why individuals become unemployed seem to play a role in how unemployment impacts well-being. In particular, transitioning into unemployment had an immediate negative effect on life satisfaction as well as the satisfaction with one's income when individuals become unemployed due to mass-layoffs or plant closures. Crucially, these negative effects exist even though individuals were able to anticipate the consequences of unemployment as they likely already expected or knew that they would lose their jobs. For individuals losing their job due to other reasons (e.g., expiring contract), these immediate effects were smaller and not significant in the case of *life satisfaction*. Further, the present study found no consistent immediate effects of entering unemployment on the examined affective and eudaimonic well-being facets. Lastly, well-being levels were generally stable within the first months of unemployment indicating a general absence of short-term adaptation.

Implications

The finding that CWB facets are more strongly impacted by unemployment than facets of other well-being domains is in line with previous research (e.g., Knabe et al., 2010). Hetschko et al. (2021) explained this phenomenon by stating that unemployment primarily leads to a loss in *identity utility*, which negatively affects CWB facets but not as much AWB or EWB facets (see also Schöb, 2013). Specifically they stated that individuals who have finished their education and are below retirement age generally consider themselves as part of the social group "working-age people", which has a strong social norm towards being employed and being able to provide for oneself (Hetschko et al., 2021). Whenever an individual breaks this social norm, they lose *identity utility*. Hetschko et al. (2014) provided empirical evidence for this theory by showing that *life satisfaction* increased when unemployed individuals reached retirement age and retired. The authors explained this finding by the idea that individuals' *identity utility* is restored due to the change in the social role from "unemployed" to "retiree". Further evidence for the role of *identity utility* comes from a study showing that formerly unemployed individuals who took up subsidized jobs gained *life satisfaction*, which was also true for individuals in subsidized jobs that entered regular employment (Hetschko et al., 2020). These results suggest that the negative effects of unemployment on well-being are mainly due to the loss of social status and personal identity, which are both central elements of Jahoda's deprivation model (Jahoda, 1982) and Warr's vitamin model (Warr, 1987).

Importantly, the results of this study *do not* indicate that unemployment does not have an effect on AWB and EWB at all. Rather, it is possible that some of the effects of unemployment will evolve over time when individuals remain unemployed for longer time periods. Specifically, long-term unemployment compared to short-term unemployment is likely to have a stronger impact on one's lifestyle (e.g., due to limited income) as well as one's psychological resources (i.e., low self-efficacy due to low re-employment prospects), which might in turn lead to more pronounced well-being changes.

Limitations and Future Research

The present study was conducted during an economic boom so that only few individuals actually entered unemployment and many of these were able to find new employment rather quickly. Thus, the dataset is not suited to examine the impact of medium- to long-term unemployment. More research is needed to better understand the role of re-employment prospects and the broader economic situation when examining the effects of unemployment on well-being. Another issue to keep in mind is that all respondents of the GJSP registered as jobseekers before the first measurement wave. Thus, it is likely that the well-being levels measured at M1 do not necessarily resemble the habitual well-being levels but that these well-being levels are already affected by the precarious employment situation of the respondents.

In the present study, we used a short version of the Ryff-Scale as the central measure for EWB. It is, however, important to note that many different conceptualizations of EWB exist (Heintzelman, 2018; Huta & Waterman, 2014) and that the presented finding might not generalize to other EWB facets. Moreover, even though we already selected those items that are most sensitive to change, the facets of the Ryff-Scale are still highly stable over time. In order to examine potential changes in EWB it seems worthwhile to incorporate EWB scales that are more sensitive to change. Particularly, the PERMA-Profiler (Butler & Kern, 2016), the Comprehensive Inventory of Thriving (CIT; Su et al., 2014) or the Well-Being Profile (WB-Pro; Marsh et al., 2020) seem to be promising instruments for this task. Moreover, we assessed meaning in life with two ad-hoc developed items in order to keep the ESM questionnaires short. Assessing meaning in life more comprehensively using validated scales (e.g., the Meaning in Life Questionnaire; Steger et al., 2006) is therefore an important task for future research on unemployment related effects on EWB.

A central finding of our study is that the reason for the job-loss can play a substantial role in how unemployment affects well-being. In order to minimize the influence of individual qualifications and characteristics on the probability of losing one's job ('selection effect'), existing research on the impact of unemployment on well-being has often focused on individuals that lost their jobs due to mass-layoffs and plant closures (Paul & Moser, 2009). However, individuals experiencing a mass-layoff also have some unique features that should be considered when interpreting the results. For instance, it is easier for employees affected by mass-layoffs to attribute their job-loss to external factors. Moreover, many (former) coworkers of respondents likely also suffered a dismissal. Existing studies showed that becoming unemployed has smaller effects on well-being if other people in the region or in the household also are or become unemployed (e.g., Clark, 2003). To investigate such context effects of unemployment, future studies could include the local unemployment rate and the employment status of other family members as moderator variables in their analyses. Moreover, additional research is needed to better understand the underlying mechanisms of how different reasons for a job-loss moderate the impact of unemployment on well-being.

Lastly, one of the main goals of this study was to design a well-controlled research design that is capable to address various threats to internal validity when deriving the immediate effects of entering unemployment. We are convinced that our approach of designing a minimalistic research design that allows probing its main assumptions is a valuable step in order to better understand how life events affect well-being. Even though the robustness checks yielded consistent results, we are well aware of the fact that the derived effects might not reflect the true causal effects of unemployment. For example, the common trends assumption might be violated by the fact that the control groups consists of individuals who (a) could keep their jobs after all and (b) individuals who lost their job but immediately started a new job before entering unemployment. In particular, it seems debatable whether the well-being changes of the “job changers” really resemble to counterfactual well-being changes of the event group. Unfortunately, the present data does not allow differentiating between job changers and job keepers so that we could not empirically examine this issue. In addition, even in the propensity score matched sample the event and control groups differed in terms of several characteristics, which also poses a threat to the common trends assumption. However, these pre-event differences seem plausible as the first measurement occasion of the present study is just shortly before the event group became unemployed so that these individuals were likely already affected by the forthcoming job-loss. To circumvent this issue, high-frequency panel studies with longer pre-event time lags are needed. Such a design would allow to identify highly similar groups of individuals who either remain employed (i.e., control group) or enter unemployment (i.e., event group). Despite these doubts on the causal nature of the effects, we are convinced that applying causal frameworks in the research on life events is a highly valuable effort, as it adequately reflects the inherently causal nature of most research questions in this domain while also promoting transparency in terms of the underlying assumptions.

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