The German Socio-Economic Panel study

991 2018

SOEPpapers
on Multidisciplinary Panel Data Research

SOEP — The German Socio-Economic Panel study at DIW Berlin 991-2018

The Causal Analysis of the Development of the Unemployment Effect on Life Satisfaction

Nils Lerch

DIW SOEP

ISSN: 1864-6689 (online)

German Socio-Economic Panel (SOEP)
DIW Berlin
Mohrenstrasse 58
10117 Berlin, Germany

Contact: soeppapers@diw.de

The Causal Analysis of the Development of the Unemployment Effect on Life Satisfaction

Nils Lerch*

Leibniz Institute for Educational Trajectories (LIfBi)

October, 2018

Abstract

The long-term negative effects of unemployment, especially on subjective well-being, have been indicated by many studies. Therefore, unemployment and its effects on the individual life course must remain an important challenge for social policy. Many studies have focused on the cognitive component of subjective well-being, i.e., life satisfaction, and have analysed in particular its development during the unemployment period. The trajectory is usually characterized by the effects of anticipation, reaction and adaption. Studies have shown different findings regarding the shape of the effect development. The present study discusses the effect development in greater detail and analyses whether the development of the effect is different depending on unemployment experience using longitudinal data from the German Socio-Economic Panel (SOEP) and applying fixed effects regressions. The findings of this study support a non-linear effect development, which begins with the anticipation of unemployment. The trend can be described by a linear function and polynomials up to the fifth degree. The introduction of a model according to modern causal analysis and the interpretation of the dynamic development of the counterfactual outcomes are the secondary focuses of the study. A detailed discussion of causal assumptions and necessary control variables is needed to reveal the effect of unemployment on life satisfaction. The SOEP provides information about employment status on a monthly basis. This study shows possibilities for using this information for the construction of control groups and treatment groups and analyses with ideal episode patterns.

Keywords: unemployment, SOEP, life satisfaction, causal analysis, FE-estimations, cognitive well-being

* Nils Lerch, Wilhelmsplatz 3, 96047 Bamberg, Germany, Email: nils.lerch@lifbi.de

1 Introduction

In the present study, the overall research question is as follows: What is the impact of unemployment on *life satisfaction (LS)*, which is the cognitive component of *subjective well-being (SWB)*? This analysis has great social relevance. Job loss has long-term and differing negative effects on the individual life course. It has long-term effects on the baseline of SWB, increases the poverty risk, increases the probability of future job losses, etc. A great number of studies have analysed the effect of *unemployment* on SWB with different focuses. Some findings are already well documented. Many studies have shown that unemployment decreases SWB (Winkelmann and Winkelmann 1998; Lucas et al. 2004; von Scheve et al. 2017). The previous SWB baseline is not achieved during unemployment and not after the unemployment period has ended (Clark et al. 2001; Lucas et al. 2004; Clark et al. 2008; Knabe and Rätzel 2011; Clark and Georgellis 2013; Hahn et al. 2015). In particular, Clark et al. (2008) showed non-linear SWB-development over the duration of unemployment. Furthermore, research has shown that unemployment events are anticipated (Clark et al. 2008). In contrast, Scheve et al. (2017) found no anticipation effects. The focuses of this study consist of three parts: (1) a discussion of causal relationships and *dynamic outcome developments*; (2) a discussion of how the *control group* and *treatment group* periods must be constructed; and finally, (3) a more detailed discussion of the shape of the development of the unemployment effect. Regarding (1), a causal model of the effect of unemployment on *LS* from a panel perspective with *fixed effect (FE) estimations* is introduced. Recent research has indicated that some further causal assumptions are needed to consider whether FE estimations are used (Morgan and Winship 2015; Imai and Kim 2016; Vaisey and Miles 2016). *Directed Acyclic Graph (DAG) analysis* (Pearl 2013) is used to discuss the causal relationships among treatments, outcomes (observed and unobserved), time-varying confounders and unobserved time-constant heterogeneity. Finally, dynamic outcome development is discussed to identify the positive or negative trends that biased the causal effect. Regarding (2), the second aim of this study is to discuss how the periods of the control and treatment groups must be constructed if employment status information is available on a monthly basis. It could be that there are some unemployment periods in the years of employment and employment periods in the years of unemployment, which can be observed between two interview times. The findings between models with *ideal patterns* and *non-ideal patterns* are compared in the analysis. Regarding (3), the main focus is on the development of the effect of unemployment on *LS* over time. Which functional shapes do anticipation, reaction and adaption effects have together?

What is the beginning of the unemployment effect: the reaction or the anticipation? When is the strongest unemployment effect? In this study, the assumed trajectory of the unemployment effect is described by different functions (linear, quadratic, etc.). Furthermore, whether the findings differ depending on the level of unemployment experience is analysed. The section entitled *Theories and Hypotheses* discusses the underlying theoretical assumptions (SWB concept; *Social Production Function (SPF) theory*; *deprivation approach*). In the section entitled *Data and Methods*, the longitudinal data used are presented. Furthermore, the chosen analysis methods (FE estimations with specific adjustments such as the use of control group information) and the causal analysis of the effect of unemployment on *LS* (DAG analysis; interpretation of the dynamic development of the counterfactual outcome) are presented. Subsequently, the complex dataset construction (the construction of the control and treatment group, the differentiation between ideal and non-ideal patterns of treatment group periods, etc.) and the variable operationalization are explained in the section entitled *Dataset construction and variable operationalization*. Finally, after the presentation of the univariate and multivariate findings, the *Discussion* section summarizes the overall findings and provides an outlook on further research questions.

2 Theories and hypotheses

First, the concept of SWB must be explained (Diener 1984). SWB is commonly known as an overall category, providing information about how individuals assess their lives as a whole. SWB is a subjective assessment of objective life conditions. Changes in life conditions change the subjective assessment. Therefore, SWB measures the consequences or effects of changes in objective life conditions. The assessment of SWB consists of an affective component and a cognitive component. The focus is on the more cognitive component and therefore on the *LS*. *LS* is a global judgement about the actual life situation. This judgement is based on permanent information and is relative to chosen social comparison standards. The SPF theory is used to explain the stability of and changes in SWB. The assessment of *LS* is based on information about the attainment of five *instrumental goals: stimulation, comfort, status, behavioural confirmation* and *affection*. Depending on resources, certain activities can be undertaken to satisfy these instrumental goals. Negative events, such as unemployment, reduce the availability of necessary resources. Instrumental goals cannot be achieved, resulting in a decrease in SWB (Diener 1984; Veenhoven 2008; von Scheve et al. 2017).

The effect of unemployment on *LS* can be explained using the deprivation approach of Jahoda (1981, 1982) Jahoda and Brandt (1986).

To become unemployed means that instrumental goals, such as status or stimulation, are not achieved compared to the previous status (explained by Jahoda using the *material and non-material impacts of unemployment*[1]).

> **H1** To become unemployed, compared to not becoming unemployed, decreases LS.

If individuals become unemployed, they will attempt to find *substitute resources* (e.g., time used for family and friends). Unemployment has a great effect on different resources and activities. Complete compensation for the loss of satisfaction due to unreached instrumental goals is unlikely. Changes in SWB, as a consequence of great negative events such as unemployment, are long-lasting and persistent. Individuals will not achieve the previous SWB baseline: (1) within the unemployment duration (Clark et al. 2001; Lucas et al. 2004; Clark et al. 2008; Knabe and Rätzel 2011; Oesch and Lipps 2011; Clark and Georgellis 2013); or (2) immediately after the unemployment period (Lucas et al. 2004; Knabe and Rätzel 2011). Regarding (1), it does not mean that there is no substitution of unavailable resources or constant/linear falling of SWB. The adaption process of SWB during unemployment is a complex trend (Georgellis et al. 2008). After a certain time of falling (first reaction, problems with the acceptance of unemployment and no suitable substitute resources), SWB will increase again (acceptance of unemployment and the use of more suitable substitute resources to satisfy instrumental goals), and a continuous process will occur, followed by alternate up and down movements (the finding of a new, reduced baseline of SWB or a possible habituation effect). Regarding (2), the cognitive assessment of SWB is still influenced by the negative effects of unemployment and is better known as the scarring effect of unemployment (Clark et al. 2001).

> **H2** The development of the negative effect of unemployment on LS over time comprises a decrease in satisfaction immediately after unemployment sets in, followed by an increase and a subsequent phase of continuous up and down movements.

In addition to the previously discussed *reaction and adaption effects*, *anticipation effects* can also appear (Uglanova and Staudinger 2013; O'Donnell et al. 2015; von Scheve et al. 2017). For several reasons (e.g., expiring contracts) it is possible that an individual anticipates his or her unemployment status and the forthcoming reduction of important resources needed to satisfy instrumental goals.

[1] Compare the remarks of Esche (2017) for a more detailed overview and for an account connected with SPF theory.

H3 The negative unemployment effect on LS can be observed before the beginning of unemployment as a result of anticipation.

Actually, the aforementioned theoretical assumptions (especially the deprivation approach of Jahoda) are more focused on employed individuals. *Employment* is a multifunctional resource in which resource income has an important function. The definition of the actual living standard regarding income and its function to satisfy different instrumental goals (especially status, comfort and stimulation) have a great effect when individuals become unemployed. Due to the strong negative effect of income reduction (third order resource) on the execution of higher-level activities and the achievement of higher-level status (second order resources), complete satisfaction of instrumental goals with other substitute resources is unlikely.

In addition, some specific interaction hypotheses are formulated. The aforementioned theoretical assumptions of H2 imply that the negative effect of unemployment increases at the beginning of unemployment.

H4 The longer an individual has already been unemployed, the stronger the negative effect of unemployment on LS at the beginning of the unemployment duration.

The theoretical assumptions of H3 imply that the negative anticipation effect of unemployment on *LS* is stronger, the closer the anticipated unemployment period is.

H5 The closer the anticipated unemployment period, the stronger the negative effect of the anticipation of unemployment on the *LS*.

3 Research design

3.1 Data and methods

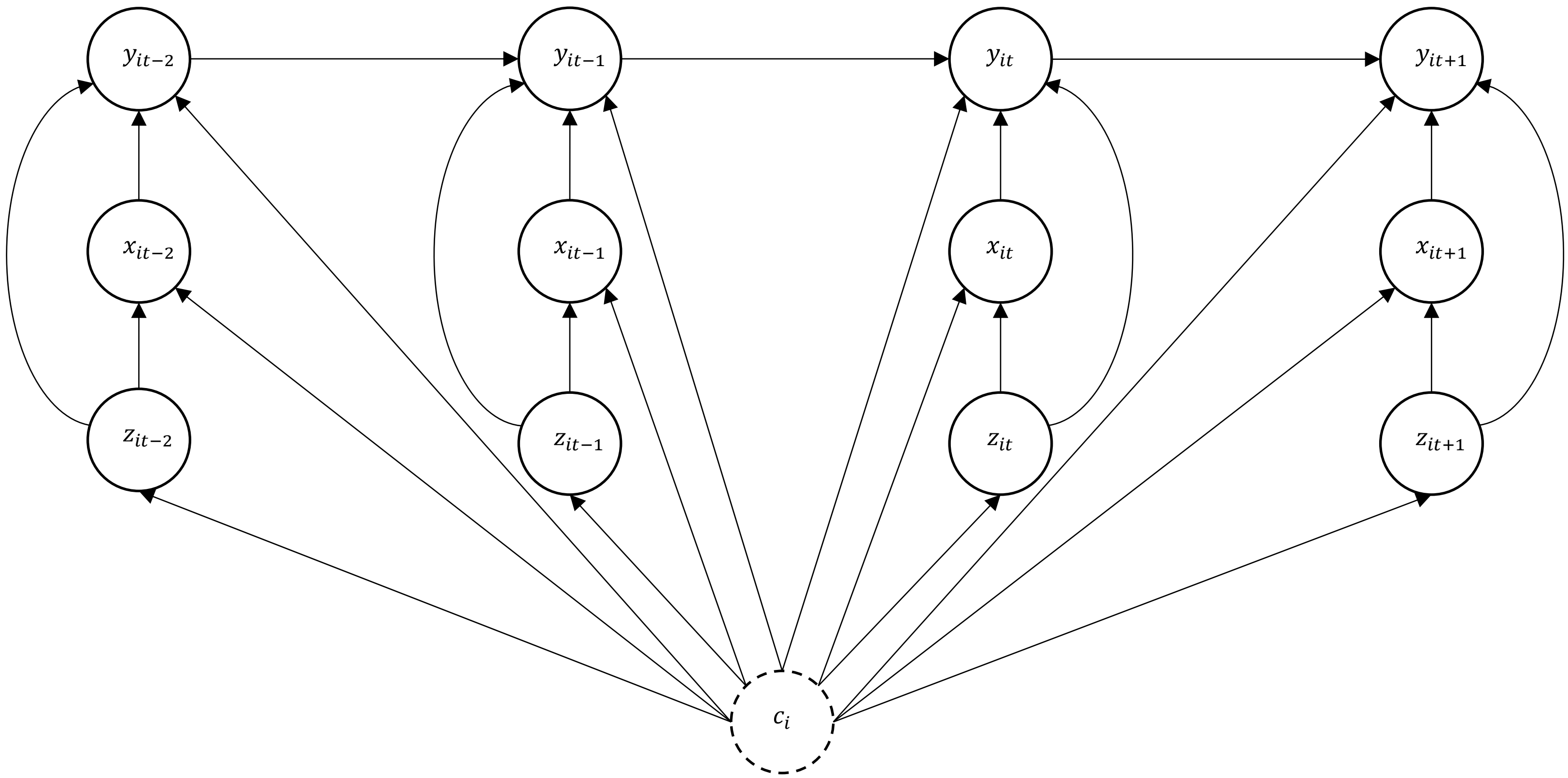
Data from the *German Socio-Economic Panel (SOEP)* (Goebel et al. 2007; Schupp et al. 2017) are used: waves a (1984) to bf (2015). All of the samples and an unbalanced panel data design are used. There is gapless information about the central independent variable of unemployment and the dependent variable of *LS*. The use of panel data for the analysis of the hypotheses has an important advantage compared to cross-sectional data: the possibility of using the *within-estimator* and the ability to overcome the problem of *unobserved heterogeneity*.

In the present study, FE estimators are used with control group information and time as a time-varying confounder. There is individual unobserved heterogeneity (e.g., motivation, intelligence, etc.) that confounds the causal effect of unemployment on *LS*. A method is needed to eliminate this bias. The fixed-effects FE estimator is suitable for this purpose. The *within-transformation* eliminates the unobserved fixed individual effects and time-invariant variables. *Hausman's test* is used to test the assumption of unobserved individual heterogeneity. If H0 cannot be rejected, then the use of *random-effects (RE) models* is better and more efficient. The simple FE estimator is biased if there are *age and period effects*. The control group information is needed to control for these effects. In general, the consideration of the control group is suitable for obtaining more reliable estimators of the control variables. The estimations are only unbiased if there is a *common baseline trend* of the treatment and control groups in the status without treatment. Finally, the use of the FE estimators is only suitable if we have sufficient intra-individual variance in the independent variable of interest (Brüderl 2010; Wooldridge 2010; Morgan and Winship 2015; Vaisey and Miles 2016; Wooldridge 2016).

The analysis of DAG and an interpretation of the dynamic outcome changes of the *counterfactual outcome* (the trend in which the treated have never received the treatment) over time are used to obtain a consistent and unbiased estimation of the causal effect. See Fig. 1: the causal graphs visualize the assumed causal relationships and assumptions, which are displayed below the graph. Furthermore, there are some trends that cause changes in the outcome. They have an effect beyond the effect of unemployment, or in other words, there is an increasing or decreasing trend in the pretreatment periods/years of non-unemployment. The important assumption is that this trajectory or slope does not differ between the treatment and control group, or in other words: *"(…) any difference between the control and treatment group – in absence of the treatment- remains constant over time (…)"* (Morgan and Winship 2015, p. 375). It is assumed that there are no different characteristics between the two groups that affect such differing trajectories. There are only persistent or constant effects of past unemployment experiences that cause a lower level of *LS* for the individuals in the treatment group. It is important to consider from a perspective of counterfactual modelling that well-specified theories are needed for theoretical assumptions about causal relationships and counterfactual trends. Well-specified, commonly known and widely discussed theories were used and are explained above. Unfortunately, in section entitled *Theories and Hypotheses,* it was assumed that there are anticipation effects, i.e., that there is a decreasing trajectory/negative slope in the pretreatment outcomes. Additional pretreatment values are chosen to overcome the problem of anticipation effects.

Furthermore, it is necessary to consider whether the unemployment effect starts with the reaction to unemployment or rather with the anticipation of unemployment (this thought is considered in the effect analysis). In addition to the aforementioned time variables, the following *time-varying confounders* are considered: (1) the *unemployment experience*; (2) the *anticipation of unemployment* periods; (3) *widowhood*; (4) *divorce*; (5) *marriage;* and (6) *the birth of a child*. Two types of time-varying confounders are considered. The *unemployment experience* is a time-varying confounder that is causal prior to the treatment and influences both current treatment and current outcome. The conditioning on unobserved time-invariant confounders and on specified observed time-varying confounders produces consistent and unbiased estimations (see Fig. 1: $x_{it} \leftarrow c_i \rightarrow y_{it}$; $x_{it} \leftarrow z_{it} \rightarrow y_{it}$). The other time-varying confounders shock the baseline trend of the outcome. They are also needed for a consistent estimation. *The unemployment experience* (1): Previous unemployment experiences have long-term/persistent and constant negative effects on *LS*. Furthermore, previous unemployment experience increases the probability of further unemployment experiences. Previous unemployment experiences confound the causal effects of unemployment on *LS*. *The anticipation of unemployment periods* (2): The anticipation of unemployment has a negative effect on the *LS*. *Widowhood* and *divorce* (3 and 4): widowhood and divorce decrease *LS*, whereby the former effect is greater than the latter effect (Clark et al. 2008). *Marriage* and *the birth of a child* (5 and 6): in contrast to the aforementioned negative events, the effects of marriage and the birth of a child increase *LS* (Clark et al. 2008). Further variables such as *income* and *health* are not considered. The aforementioned theoretical assumptions interpret both variables as *mechanism* (D→A→Y), explaining a part of the causal effect of unemployment on *LS*. Unemployment causes a decrease in income (material consequences of unemployment) and deterioration of health (non-material consequences), and these effects cause a decrease in *LS*. Income and health as intermediary mechanisms are not controlled in the model, as the full causal strength would be underestimated. Furthermore, the probability of conditioning on *collider variables* would be increased: *"Conditioning on a collider variable that lies along a back-door path does not help to block the back-door path but instead creates new associations"* (Morgan and Winship 2015, p. 107).

Health can also be interpreted as a time-varying confounder if it is assumed that bad health increases the likelihood of unemployment. However, this mechanism is more likely.



Causal assumptions (1) There are no unobserved time-varying confounders; (2) There are unobserved time-invariant confounders; (3) Past treatments do not directly affect current outcomes; (4) Current outcomes do not directly affect current treatments (there is no self-selection on the treatment effect); (5) Past outcomes do not directly affect current treatments (there is no negative or positive selection on the pre-treatment outcome); (6) Past treatments do not directly affect current treatments; (7) There are some observed time-varying confounders
Legend y_{it}: current outcome (*LS*); x_{it-1}: past (one year ago) treatment (*unemployment*); z_{it+1}: observed future (next year) time-varying confounder (e.g. *unemployment experience*); c_i: unobserved time-invariant individual heterogeneity

Fig. 1 Graphical visualization of the causal effect of unemployment on LS (own illustration)

3.2 Dataset construction and variable operationalization

At the beginning of the following section, the first task is to define who is unemployed and who is not. Retrospective information[2] (for the previous calendar year) about the employment status for each month was used to construct the variable of unemployment (0 – not unemployed; 1 - unemployed)[3]. Not only one (main) employment status was collected but rather information about simultaneously tracked types of different employment statuses. For example, an individual can have the employment status of *full-time employed* and, at the same time, the employment status of *maternity leave*. However, there are also impossible combinations. For example, an individual cannot have the employment status of *full-time employed* and at the same time the employment status of *registered unemployed*. A slightly modified version[4] of the table from Esche (2017) was used for a *plausibility check* and *priority assignment* (see Appendix, Table A1). Only individuals between 18 and 64 years of age were considered. The variables of unemployment and group membership (control or treatment group) are mainly constructed by the calendar month information from *ARTKALEN*. The individuals are either in the control group or in the treatment group. Individuals in the control group are always in the status of 0 over all of the survey years. See Appendix, Table A2: the control group has the following patterns across all of the calendar months of the survey year *2000*: 000000000000. The same procedure is used for each observed year of an individual in the control group. Therefore, only one episode exists for individuals in the control group. Individuals in the control group are deleted from the dataset if there is a calendar month in unemployment, if there is a missing value, if there are previous unemployment periods before the first observed survey year[5], if there is a month on pension and if the month on pension does not mark the final transition of the pension phase. Individuals in the experimental group sometimes have status of 0 and sometimes status of 1 over the survey years.

See Appendix, Table A2: the experimental group has the following patterns for all of the calendar months of the survey year *2001*: 000000011111.

---

[2] You can find the information in the employment spell dataset *ARTKALEN* (Goebel 2017).

[3] At this point in time of the dataset construction, the distinction between employed and unemployed has not yet been implemented. *Maternity leave*, *Civil or military service*, *Initial training*, *School/ University*, *Full-time employed*, *Marginal/part-time employment*, *Other*, *Housewife/-husband*, *In-company advanced training*, and *Short-time work* are assigned to 0 - not unemployed. *Registered unemployed* is assigned to 1 - unemployed. *Pension* and *missing values* are characterized as missing values.

[4] The employment types *In-company advanced training* and *Short-time work* were considered.

[5] The information for this adjustment rule is based on the spelling file *PBIOSPE* (Goebel 2017).

In contrast to the control group, individuals in the experimental group can have more than one episode over the survey years. The individuals in the treatment group are deleted from the dataset if there are missing values between the interview months of the last year in non-unemployment and the first year in unemployment (all previous years in non-unemployment or following years of unemployment are deleted from the dataset; where it is not true, there are no missing values between the first interview month and the last interview month of a period) and if there is a month on pension and this month on pension does not mark the final transition in the pension phase. If the individual is in the experimental group or in the control group and if there are no biographic information[6], then the individual is removed from the dataset. The focus of the analysis is on the employment statuses of *employed* (full-time, part-time/mini-job). An individual in the control group must be permanently (across all calendar months of the survey years) employed. An individual in the experimental group must be permanently employed across all of the calendar months of the survey years in non-unemployment. Furthermore, the months in non-unemployment (if non-ideal patterns are used for the analysis) in the years of unemployment must be months in the status of *employed*. That is, between the first interview month in unemployment and the last interview month in unemployment, an individual in the treatment group must have the status of employed. Survey years below and above this interval are cut off. In the following, the operationalization of the dependent variable (1), help variables (2), control variables (3), interaction variables (4) and unemployment variables (5) is presented (see Fig. 2).

(1)

LS: LS is measured with the question "How satisfied are you with your life, all things considered?" and the possible answers range from 0 (completely dissatisfied) to 10 (completely satisfied). *LS* is interpreted as an interval-scaled variable, although it is an ordinal variable. The more categories, the more the variable can be interpreted as quasi-metric, and the more the means will be useful (Wagner 2007; Hajek 2011; Kühnel and Krebs 2014).

---

[6] There are some time periods in SOEP when the biographic questionnaire was not systematically integrated. This was especially true for samples *A* and *B* (systematically integrated since 1988) and *C* (systematically integrated since 1992). If there was no information about the occupational biography, which was collected with the biography questionnaire, then it could be that the individual was too young at entry into the SOEP. In *Documentation on Biography and Life History Data* (Goebel 2017), there is information with which to sort out individuals with missing biographic information.

(2)

The identification of years in non-unemployment and unemployment (h1): The variable *h1* is consistent over all individuals in the experimental group and for each episode of all of them in employed (*h1*= -30 to -1) and unemployed years (*h1*= 0 to +47). For example (see Fig. 2), if *h1* has the value of +1, the individual is in the second unemployment year after the year in which the individual became unemployed (*h1*=0).

The selection of ideal employment- and unemployment-patterns (h2): Unemployment trajectories do have not ideal patterns such as 000000111111 but rather non-ideal patterns such as 111001011100 (see Fig. 2: y5). The trajectories are characterized by many changes between the two states. *h2* distinguishes these patterns. All of the survey years of an individual are used for the analysis when it is known that the individual is employed from the first observed interview month in employment until the first observed calendar month in unemployment, that the individual remains unemployed until the first observed interview month in unemployment (see Fig. 2: *h1*= -2 to 0) and that the individual remains unemployed from the first observed interview month in unemployment until the last observed interview month in unemployment (see Fig. 2: *h1*=0 to +1). If the pattern of a survey year is ideal, *h2* obtains the value of 0 (see Fig. 2: *h1*= -2 to +1). If the individual does not remain unemployed from the first observed calendar month in unemployment until the last observed interview month in unemployment, the relevant non-ideal survey year and all of the survey years thereafter obtain the value of 1 on the variable *h2* (see Fig. 2: *h1*= +2). If the individual does not remain employed from the first observed calendar month in unemployment until the first observed interview month in employment, the relevant non-ideal survey year and all of the previous survey years obtain the value of 1 for the variable *h2*. If the individual has a value of 1 for the variable *h2* and if this marker concerns the value -1 or 0 for the variable *h1*, then the whole episode (each survey year) of the individual obtains the value of 1 for the variable *h2*.

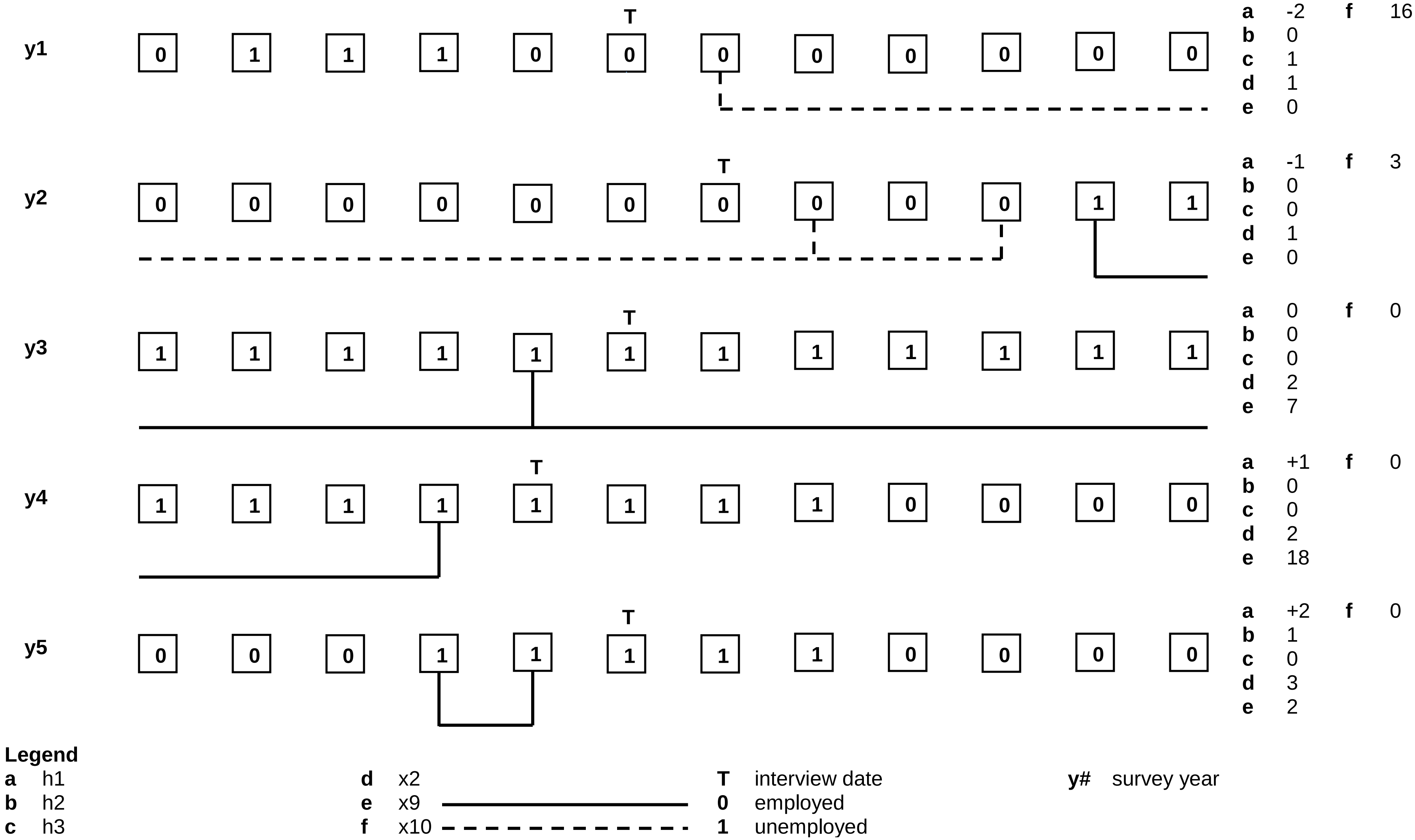


Fig. 2 Description of different variable operationalizations (own illustration)

Missing identifier (h3): Cases with a missing value for one or more variables at a specific point in time are not considered in the analysis. Therefore, it is necessary to control the cases that remain in the dataset. In the following, some rules are presented. Each case of the control or treatment group obtains the value of 1 on *h3* if there is a missing value. If there is no missing value, then each case obtains the value of 0. Only individuals in the control group with two remaining years are considered. If an individual in the treatment group has a missing value for the values of -1 or 0 of the variable *h1*, then the whole episode is not considered in the analysis. See Fig. 2: there is a missing value in survey year 1. Therefore, variable *h3* has the value of 1.

(3)

The anticipation of an unemployment period (x1): This variable identifies the anticipation effects of unemployment phases in the surveyed years of employment (*h1*= -30 to -1). The variable *x1* has the value of 1 if an individual in the experimental group becomes unemployed between the interview month and the next interview month. See Fig. 2: the individual becomes unemployed between the interview month in survey year 2 (*h1*= -1) and the interview month in survey year 3 (*h1*=0). Therefore, variable *x1* has the value of 1 in survey year 2 (*h1*= -1). In some hypothesis tests, this variable is split into several parts. If whether unemployment is anticipated one (*h1*= -1) or two (*h1*= -2 and -1) years before individuals become unemployed is to be analysed, then single independent dummy variables must be generated. In addition, one further variable is needed to identify anticipation effects in other non-unemployment years (*h1*= -30 to -3 or -2) if non-ideal patterns are used for the analysis.

Unemployment experience (x2): This variable is counted and identities for each survey year the unemployment experience of the treatment group, which started before the interview date. The information about unemployment phases before the first observed survey year comes from *PBIOSPE*. See Fig. 2: It is assumed that there are no unemployment periods before the first observed survey year in non-unemployment (*h1*= -2). However, there is an unemployment period before the first observed interview month in employment. Therefore, *x2* has the value of 1. The same value has the following survey year in employment (*h1*= -1). In the first observed survey year in unemployment (*h1*=0), *x2* has the value of 2 because the individual experienced a new additional unemployment period. In survey year four, the value of *x2* remains the same, but in survey year five, a new unemployment period has started. Therefore, the variable *x2* has the value of 3.

Age of the individual (x3): The age variable is generated by the subtraction of survey year and year of birth.

Periods (x4): t1 (1984)-t31 (2014) are the survey year dummies. If we control for age and periods, we obtain the *Age-Period-Cohort (APC) problem*. It is not possible to control for all of them together in a linear regression model. The FE model controls implicitly for the birth cohort (the birth cohort is constant over the periods of an individual). Age and period are perfectly collinear. The problem is solved with the introduction of restrictions (Brüderl 2010). An estimation of the period effects on *LS* shows that the most negative effects are during *2004-2009* (>= -0.8). These periods are included in the analyses. The other periods build the reference category (see Appendix, Table A3).

Widowhood (x5); divorce (x6); marriage (x7); the birth of a child in the household (x8): The mentioned *shock events*[7] are operationalized as dummy variables (0: not observed; 1: observed).

(4)

How long an individual is already unemployed (x9): This variable indicates how many months an individual is already unemployed before the observed interview months in unemployment. See Fig. 2: the individual is already unemployed for seven months.

How long an individual is employed before the first unemployment month (x10): The variable *x10* considers the months in employment until the first calendar month in unemployment. See Fig. 2: the individual was employed for three months before the first observed calendar month in unemployment.

(5)

Employment status with M1 or M2: Different operationalizations of unemployment are needed for the analyses. A dummy variable is needed to define the individuals who are 0 *employed* or 1 *unemployed* in the survey years. See Fig. 2: if an individual is employed at the interview (T), then the dummy has the value of 0. If an individual is unemployed at the interview (T), then the dummy has the value of 1. For the hypothesis tests and especially for the *step impact and continuous impact functions* (Andreß et al. 2013), it is necessary to identify the employment and unemployment years. In this study, two methods are used. The first method (*M1*) uses the values of the variable *h1*. If *h1* has the value of 0, then the reaction effect on unemployment is observed. If *h1* has the value of +5, then the adaption process of unemployment in the sixth year in unemployment (five years after the individual became unemployed) is observed. The second method (*M2*) uses the values of the variables *x9* (reaction and adaption) and *x10* (anticipation). With these values, a more detailed view on the unemployment duration can be obtained.

[7] Clark et al. (2008) showed that the strongest effects are at entry into unemployment.

M1 identifies the reaction effect on unemployment with the value of 0 of the variable *h1*, but it is possible that the individual is already unemployed for 12 months. In *M2*, the reaction effect is identified if there is no previous month in unemployment (+0). The same focus is applied to the anticipation of unemployment. The immediate anticipation effect is identified if the following month is a month in unemployment (-0). Before (-0) and after (+0), one year intervals are generated. If *x10* (anticipation) has the value of 9, then the specific survey year in employment falls in the interval of *-1 (-12 to -1)*. If *x9* has the value of 16, then the specific survey year in unemployment falls in the interval of *+2 (+13 to +24)*. *M1* is the method mainly used because it can be applied for analyses with ideal patterns, as well as for analyses with non-ideal patterns. *M2* can only be used for analyses with ideal patterns. *M2* is used for a more detailed view of the development of the unemployment effect and for the development of the unemployment effect depending on unemployment experience.

4 Findings

4.1 Description of the analysis dataset and univariate analyses of used variables

This section starts with a description of the analysis dataset and a univariate analysis of the variables used. The statistics differ depending on whether the focus is on the treatment group, control group or total value across both groups. Furthermore, the statistics of the treatment group and the total value across both groups differ depending on whether the focus is on ideal patterns or non-ideal patterns. See Appendix, Table A6, serial numbers 1 and 2: if non-ideal patterns are used, then the analysis dataset consists of 84,428 person-years (control group: 52,024; treatment group: 32,404) and 11,797 individuals (control group: 7342; treatment group: 4455) across the treatment and control groups (see column *Total*). If ideal patterns are used, the analysis dataset is reduced to 80,150 person-years (control group: 52,024; treatment group: 28,126) and 11,047 individuals (control group: 7342; treatment group: 3705) across the treatment and control groups. See Appendix, Table A4, serial number 1: the average number of both groups is approx. 7 (control group: approx. 7; treatment group: approx. 7) with a high standard deviation of approx. 5 (control group: approx. 6; treatment group: approx. 5), with a minimal spell number of 2 and a maximal spell number of 31 if non-ideal patterns are used, as well as if ideal patterns are used. See Appendix, Table A4, serial number 4: for both ideal patterns and no ideal patterns, the averaged spell number across all of the periods of the treatment group is approx. 6 with a standard deviation of approx. 4.

See Appendix, Table A6, serial number 8: if non-ideal patterns are used, there is 21.35 percent of the treatment group with more than one period (19.33 percent if ideal patterns are used). The number of periods is a minimum of 1 and a maximum of 7 for both patterns.

The dependent variable *LS* is described in Appendix, Table A4, serial numbers 3, 5 and 6 (see Appendix): the averaged *LS* across both groups is approx. 7, 8 for the control group and 6 for the treatment group. The treatment group has an averaged *LS* of approx. 7 in the years of non-unemployment and a value of approx. 6 in the years of unemployment for both patterns. The standard deviation is always approx. 2. See Appendix, Table A4, serial number 10: the averaged *LS* in years of non-unemployment is less for those individuals who have unemployment experience (*x2*=0-6) with a tendency towards a decreasing trend as the unemployment experience increase. See Appendix, Table A4, serial number 11: for the average *LS* development in years of unemployment depending on unemployment experience (*x2*=1-7), the same interpretation applies as for the average *LS* development in years of unemployment. The analyses in serial numbers 10 and 11 in Appendix, Table A4 are restricted to the first seven levels of unemployment experience because the number of observations is, on the seventh level, already less than 100.

Appendix, Table A6 and serial number 1 (see Appendix) present the central independent variable *unemployment*. If non-ideal patterns are used, then 21,370 (ideal patterns: 18,700) person-years in non-unemployment and 11,034 (ideal patterns: 9426) person-years in unemployment are observed. See Appendix, Table A5: if method *M1* is used, then individuals can be observed for 30 years in non-unemployment before they become unemployed (346 months in employment if *M2* is used), and they can be observed for 17 survey years in unemployment (203 months in unemployment if *M2* is used). This outcome applies to both non-ideal patterns and ideal patterns. The greatest frequencies are at -1 (one year before the individual become unemployed) and 0 (the individual become unemployed) for both methods *M1* and *M2*. At this point, the first large differentiation between non-ideal patterns and ideal patterns can be seen. This differentiation concerns the number of observed unemployment years if ideal patterns are used (*h1*=0 to +16). The more time of becoming unemployed has passed, the more the number of observations decreases.

Compared to the use of non-ideal patterns, only approx. two-thirds of the number of observations can be used if the analysis consists of ideal patterns. The small number of observations can restrict the analysis of the development of the unemployment effect on *LS* (Hypotheses 2). The reduction in the observations of years in non-unemployment (*h1*= -30 to -1) is not as great as in the years of unemployment.

In the following, the control variables are presented. See Appendix, Table A4, serial number 7: if non-ideal patterns are used, then the averaged *unemployment experience* of the treatment group and the standard deviation are higher than for ideal patterns (non-ideal patterns: Mean 2.25 and Std. Dev. 1.62; ideal patterns: Mean 2.06 and Std. Dev. 1.42). The maximal value of *unemployment experience* is greater for the treatment group with non-ideal patterns (non-ideal patterns: 15; ideal patterns: 13). See Appendix, Table A6, serial number 7: if non-ideal patterns are used, then individuals in the treatment group can be observed who *anticipate unemployment* in all years of non-unemployment. If ideal patterns are used, then the observation of *anticipation effects* is restricted for the last year in non-unemployment before the individual becomes unemployed. Therefore, the number of such events is greater for non-ideal patterns (6426) than for ideal patterns (5428; it is the same number as the value of 30 for variable *h1*: see Appendix, Table A5). If ideal patterns are used, then the control for the *anticipation effect* is the same as choosing the year before becoming unemployed as the start of the unemployment effect. Then, the comparison of the *anticipation effect* and the effects of each unemployment year is performed with the non-unemployment years *h1*= -30 to -2 (30 years to 2 years before the individual becomes unemployed). See Appendix, Table A4 serial number 2: the average *age* of all individuals, person-years, groups and patterns is approx. 43 or 44 with a standard deviation of approx. 9 to 11. The *age* is restricted to 18 to 64 years old. See Appendix, Table A7: there are 31 *periods,* and it can be seen on the frequencies across both groups that the observations per *period* have doubled since 2000. The frequency distribution of the treatment group reflects the general distribution of the years in non-unemployment and unemployment presented in Appendix, Table A5. See Appendix, Table A6, serial numbers 3-6: the last four control variables – *widowhood*, *divorce*, *marriage* and *child births* -- are presented together with the percentage values of occurred events. The first observation is that there is no great difference between the two forms of patterns across all of the variables. The second observation is that there is also no great difference between the treatment and control groups. Viewed across both groups, the most observed events are *birth of a child* and *marriage*. Very few events are observed for the event of *widowhood*.

The interaction variables (how long an individual is already unemployed (*x9*) and how long an individual is employed before the first unemployment month (*x10*)) are only considered in the analysis of ideal patterns. See Appendix, Table A4, serial numbers 8 and 9: individuals in the treatment group are on average already unemployed for approx. 5 months if they become unemployed. This value varies with a standard deviation of approx. 4. The minimal observed value is 0, and the maximal observed value is 17.

The average duration from the last interview month in employment until the first unemployment month is approx. 6 with a standard deviation of 4, whereby the minimal observed duration is 0 and the maximal duration is 18. If all years in employment and unemployment are considered, then the maximal observed duration for *x9* is 202 months, and the maximal observed duration for *x10* is 345.

See Appendix, Table A8: an overall finding is that there is sufficient within variation regarding the variables used to run an FE estimation. The lowest within variation is registered for the variables of divorce and widowhood. This outcome applies to both patterns.

4.2 Multivariate analyses

Control group information and time are integrated into the model, as *LS* shows a decreasing trend over time in the data[8]. FE estimation is preferred to RE estimation because *Hausman's test* shows a systematic difference between both (FE and RE) estimations. That is, there is time-constant individual heterogeneity that confounds the causal effect of unemployment on *LS*. The following analyses are differentiated by the form of the patterns (ideal patterns and non-ideal patterns) and whether the anticipation effects of unemployment are considered or not. The consideration of anticipation effects has an important consequence. If the anticipation dummy is not considered, then the satisfaction levels in unemployment are compared to the satisfaction levels with employment up to one year before unemployment (*h1*= -30 to -1). If the anticipation dummy is considered, then the satisfaction levels in unemployment are compared to the satisfaction levels in employment up to two years before unemployment (*h1*= -30 to -2). Therefore, the unemployment effects are interpreted as starting with the anticipation of unemployment. An effect is significant at a *significance level* of 95% ($p=0.05$). *Panel robust standard errors* (S.E.s) are used (Brüderl 2010). The *within-*R^2 is displayed for each model in the tables. First, the hypotheses testing is performed with *M1*. Some additional tests, which mainly use *M2*, appear at the end of this section.

[8] Analysed with a *growth curve model* of *age* on *LS*

H1

In hypothesis 1, the aim is to identify the causal effect of *becoming unemployed*. Therefore, only the first year of unemployment (*h1*=0) and all years in employment (*h1*=-30 to -1) are considered. In Table 1, the successive model construction is performed with ideal patterns. The unemployment effect is -0.765. The control of *age* and *periods* decreases the effect to -0.673. Without controlling for time, the unemployment effect is overestimated because there are negative time trends that must be considered. The inclusion of *unemployment experience* reveals a suppressor effect and increases the effect to -0.724. The control of the event dummies *marriage*, *birth of a child*, *widowhood* and *divorce* increases the negative effect to 0.725. If *anticipation* is considered a negative shocking event and part of the general unemployment effect, then the control increases the negative effect to 0.805. All of the effects are significant in terms of content. All of the effects except for *divorce* and *birth of a child* [9] are statistically significant. *Widowhood* has the strongest negative effect and *marriage* the strongest positive effect. There are no great differences between non-ideal patterns and ideal patterns (0.01-0.02). The unemployment effects are greater if ideal patterns are used. However, the unemployment effect differences are greater between the models with and without the anticipation effect (approx. 0.08 difference). If the anticipation effect of unemployment is not considered, and ideal patterns are used, to become unemployed, in comparison to be employed, decreases the *LS* by 0.725 (non-ideal patterns: 0.711) on the *LS* scale (from 0-10), ceteris paribus (c.p.). If the *anticipation effect of unemployment* is considered, and ideal patterns are used, to become unemployed, in comparison to be employed, decreases the *LS* by 0.805 (non-ideal patterns: 0.790) on the *LS* scale, c.p.

[9] The effect *birth of a child* is significant if the analysis is not limited to the reaction effect on unemployment.

Table 1 The identification of the causal effect of becoming unemployed on *LS*

	Ideal patterns			
	(1) *LS*	(2) *LS*	(3) *LS*	(4) *LS*
Employment status (M1):				
-30 to -1 (employed)	Ref.	Ref.	Ref.	Ref.
0 (becomes unemployed)	-0.765***	-0.679***	-0.673***	-0.724***
The age in years (x3)	-	-0.0318***	-0.0298***	-0.0309***
Periods (x4):				
1984-2003 and 2010-2014	-	-	Ref.	Ref.
2004	-	-	-0.236***	-0.239***
2005	-	-	-0.0948***	-0.0975***
2006	-	-	-0.156***	-0.158***
2007	-	-	-0.0899***	-0.0922***
2008	-	-	-0.0526*	-0.0549*
2009	-	-	-0.170***	-0.172***
Unemployment experience (x2)	-	-	-	0.0515*
Widowhood (x5):				
not widowed	-	-	-	-
Widowed	-	-	-	-
Divorce (x6):				
not divorced	-	-	-	-
divorced	-	-	-	-
Marriage (x7):				
not married	-	-	-	-
married	-	-	-	-
Birth of a child (x8):				
no birth	-	-	-	-
birth	-	-	-	-
Anticipation of unemployment (x1):				
no anticipation	-	-	-	-
anticipation	-	-	-	-
_cons	7.251***	8.621***	8.564***	8.600***
N	76,152	76,152	76,152	76,152
R^2	0.023	0.034	0.036	0.036

Table 1 (continued)

	Ideal patterns		*Non-ideal patterns*	
	(5) *LS*	(6) *LS*	(7) *LS*	(8) *LS*
Employment status (M1):				
-30 to -1 (employed)	Ref.	Ref.	Ref.	Ref.
0 (become unemployed)	-0.725***	-0.805***	-0.711***	-0.790***
The age in years (x3)	-0.0304***	-0.0291***	-0.0303***	-0.0288***
Periods (x4):				
1984-2003 and 2010-2014	Ref.	Ref.	Ref.	Ref.
2004	-0.238***	-0.234***	-0.233***	-0.228***
2005	-0.0987***	-0.0950***	-0.103***	-0.0991***
2006	-0.157***	-0.157***	-0.161***	-0.160***
2007	-0.0916***	-0.0903***	-0.0951***	-0.0939***
2008	-0.0538*	-0.0523*	-0.0544*	-0.0527*
2009	-0.169***	-0.166***	-0.173***	-0.171***
Unemployment experience (x2)	0.0517*	0.0518*	0.0426*	0.0430*
Widowhood (x5):				
not widowed	Ref.	Ref.	Ref.	Ref.
widowed	-1.379***	-1.378***	-1.380***	-1.380***
Divorce (x6):				
not divorced	Ref.	Ref.	Ref.	Ref.
divorced	-0.0203	-0.0185	-0.00426	-0.00374
Marriage (x7):				
not married	Ref.	Ref.	Ref.	Ref.
married	0.248***	0.248***	0.238***	0.237***
Birth of a child (x8):				
no birth	Ref.	Ref.	Ref.	Ref.
birth	0.0633	0.0644	0.0618	0.0628
Anticipation of unemployment (x1):				
no anticipation	-	Ref.	-	Ref.
anticipation	-	-0.157***	-	-0.158***
_cons	8.576***	8.534***	8.537***	8.491***
N	76,152	76,152	79,124	79,124
R^2	0.038	0.039	0.038	0.039

SOEP data; waves a (1984) to bf (2015); own calculation; FE-estimations; the within-R^2 and panel robust S.E.s are used.

* $p < .05$, ** $p < .01$, *** $p < .001$

H2 and H3

Due to the smaller case number in the upper unemployment years, it is necessary to decide which unemployment years should be part of the analysis. See Appendix, Table A9: the development pattern of the effects over time is equal between the two patterns until the ninth year of unemployment (+8), and all of the effects are significant, regardless of whether *anticipation effects* are considered in the analysis or not. While the effect strengths seem to be equal between the patterns up to the fourth year of unemployment (approx. 0.00-0.02 difference), the differences increase beginning in the fifth year of unemployment. In particular, the differences in the eighth and ninth years in unemployment are large (approx. 0.08-0.10 difference). In the upper unemployment years, with smaller case numbers, the effects seem to be biased due to changes in employment and unemployment if non-ideal patterns are used. Therefore, the further analysis of H2 is based on ideal patterns. The effect differences between the models with and without a*nticipation effects* remain approx. 0.07-0.08 across all of the unemployment years up to the ninth year of unemployment. The visualization of the development of the unemployment effect on *LS* is accomplished by the model with the anticipation effect. First, the effect development is interpreted with a step impact function. See Fig. 3: *LS* decreases up to the second year of unemployment (+1). Then, *LS* increases in the third year of unemployment (+2). In the fourth year, *LS* decreases again (+3) and then increases up to the eighth year of unemployment (+7). Finally, *LS* decreases again. The trajectory of the unemployment effect up to the fourth year in unemployment can be interpreted as the aforementioned substitution of lost resources and is an indicator that the lost resources cannot be fully substituted through other resources.[10] The further trajectory can be described as the aforementioned alternate up and down movements. The assumed unemployment effect development is fully satisfied: The trajectory describes a fall, a rise and then a trend of alternate up and down movements. The effect development is similar if non-ideal patterns are used (see Appendix, Fig. A1). Next, the analysis is extended with the integration of the *anticipation effect* at the start of the general unemployment effect. Therefore, it is necessary to extract the anticipation variable from the general *anticipation of unemployment directly before the effect of becoming unemployed* (*h1*=0) and – if non-ideal patterns are used for the analysis -- in *anticipation events of unemployment in the other employment years* (*h1*= -30 to -2).

[10] The trajectory up to the ninth year in unemployment can be interpreted in the same manner but as a longer substitution process.

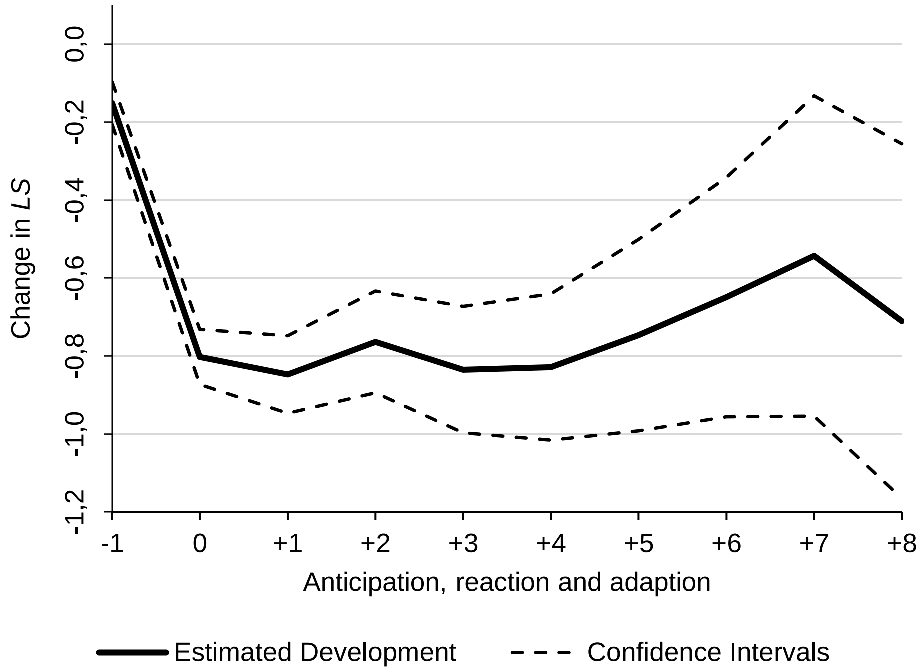


Fig. 3 The development of the causal effect of unemployment on *LS* over time: Anticipation, reaction and adaption effects if ideal patterns are used. *Note*: SOEP data; waves a (1984) to bf (2015); own illustration; data of Table 2 and Model 1.

See Table 2: if ideal patterns are used, Model 1 is equal to Model 2 in Table A9 (see Appendix). If non-ideal patterns are used, Model 3 shows that both *anticipation effects* have significant effects on *LS*. If the *anticipation event of unemployment in the years of non-unemployment* (*h1*= -30 to -2) is considered, then it exerts a suppressor effect and increases the single effects of unemployment on *LS*. If ideal patterns are used for the analysis (see Model 1), the anticipation of unemployment, compared to being employed, decreases *LS* by 0.151 on the *LS* scale, c.p. Table A10 (see Appendix) extends the analysis with ideal patterns with an additional *anticipation effect two years before unemployment* (+2). The *anticipation effect* is not significant in terms of content and is also statistically insignificant. See Fig. 3: the integration of the *anticipation effect* shows the development between the anticipation of unemployment and the reaction on unemployment. The graphic visualization supports the assumed shock of unemployment (see Appendix, Fig. A1: the effect development is similar if non-ideal patterns are used).

Table 2 The development of the causal effect of unemployment on *LS* over time: visualized as step impact function and the anticipation interpreted as the beginning of the development of the unemployment effect

	Ideal patterns	*Non-ideal patterns*	
	(1) *LS*	(2) *LS*	(3) *LS*
Employment status (M1):			
-30 to -2 (employed)	Ref.	Ref.	Ref.
-1 (anticipates unemployment)	-0.151***	-0.141***	-0.153***
0 (becomes unemployed)	-0.802***	-0.783***	-0.791***
+1	-0.847***	-0.821***	-0.828***
+2	-0.764***	-0.763***	-0.769***
+3	-0.835***	-0.830***	-0.836***
+4	-0.828***	-0.787***	-0.792***
+5	-0.747***	-0.774***	-0.779***
+6	-0.649***	-0.665***	-0.669***
+7	-0.543**	-0.441*	-0.445*
+8	-0.710**	-0.630**	-0.635**
Anticipation of unemployment (x1):			
no anticipation	-	-	Ref.
Anticipation	-	-	-0.206***
N	80,029	84,259	84,259
R^2	0.046	0.047	0.047

SOEP data; waves a (1984) to bf (2015); own calculation; FE estimations; the within-R^2 and panel robust S.E.s are used; further control variables (*x2*-*x8*) have been considered but are not displayed above.

* $p < .05$, ** $p < .01$, *** $p < .001$

Therefore, the development of the unemployment effect on *LS* can be described through a linear function and polynomials up to the fifth degree, which can be displayed through continuous impact functions. All of the continuous impact functions are statistically significant. See Table 3 and Model 1: with each additional year in unemployment, *LS* decreases linearly by 1.222, increases quadratically by 0.749, decreases cubically by 0.200, increases according to a fourth-degree polynomial by 0.0238 and decreases according to a fifth-degree polynomial by 0.00103 on the *LS* scale, c.p. The effects are approx. equal if non-ideal patterns are used.

Some tests show that the development of the unemployment effect remains stable across different restrictions: only the first observed unemployment period of an individual; only the second observed unemployment period of an individual; only individuals who remain unemployed up to the ninth year in unemployment; only those individuals who become unemployed for the first time and their first unemployment period; only individuals with ideal patterns; only individuals with non-ideal patterns; only the male gender; and only the female gender[11].

H4 and H5

Next, the interaction-hypotheses are analysed. Only ideal patterns are used for the analyses. The effect analysis could be biased if non-ideal patterns are used because unemployment periods between *anticipation* (-1) and *becoming unemployed* (0) could be anticipated.

See Table 4: as shown in previous models, the control of *anticipation effects* or *life events* increases the unemployment effect. Both models show that the interaction effect of *becoming unemployed* and *the number of already existing unemployment months* (*x9*) is significant in terms of content, and the effect is statistically significant. Model 2 with an integrated *anticipation effect* is used for the effect interpretation. Becoming unemployed, compared to being employed, decreases *LS* by 0.736 on the *LS* scale, c.p., if *the number of already existing unemployment months* is zero. Becoming unemployed, compared to being employed, decreases *LS* by 0.7615 on the *LS* scale, c.p., if *the number of already existing unemployment months* increases by one month. The *effect of becoming unemployed* decreases with each additional month by 0.0255.

[11] Clark et al. (2008) showed that the negative effects are stronger for men than for women. Furthermore, their findings suggest that men adapt less quickly to these events.

Table 3 The development of the causal effect of unemployment on *LS* over time: visualized via continuous impact functions and the anticipation interpreted as the beginning of the development of the unemployment effect

	Ideal patterns	*Non-ideal patterns*	
	(1) *LS*	(2) *LS*	(3) *LS*
Employment status (M1):			
-30 to -2 (employed)	Ref.	Ref.	Ref.
-1 (anticipates unemployment)	-0.152***	-0.141***	-0.154***
The development of the unemployment effect over time:			
Linear function	-1.222***	-1.203***	-1.195***
Quadratic function	0.749***	0.739***	0.736***
Cubic function	-0.200***	-0.198***	-0.197***
Fourth degree polynomial	0.0238***	0.0237***	0.0236***
Fifth degree polynomial	-0.00103***	-0.00102***	-0.00102***
Anticipation of unemployment (x1):			
no anticipation	-	-	Ref.
anticipation	-	-	-0.207***
N	80,029	84,259	84,259
R^2	0.046	0.047	0.047

SOEP data; waves a (1984) to bf (2015); own calculation; FE estimations; the within-R^2 and panel robust S.E.s are used; further control variables (*x2*-*x8*) have been considered but are not displayed above.

* $p < .05$, ** $p < .01$, *** $p < .001$

This finding supports the assumption of the decreasing trend at the beginning of the development of the unemployment effect. Next, H5 is analysed. See Table 4 and Model 3: the interaction effects of *anticipation of unemployment* and *the distance to the first unemployment month* (*x10*) are statistically significant as well as in terms of content. Anticipating unemployment, compared to being employed, decreases *LS* by 0.260 on the *LS* scale, c.p., if *the distance to the first unemployment month* is zero. Anticipating unemployment, compared to not anticipating it, decreases *LS* by 0.2406 on the *LS* scale, c.p., and if *the distance to the first unemployment month* increases by one month. The *anticipation effect* decreases with each additional month by 0.0194. The closer that the negative event is, the stronger that the negative impact on the *LS* is.

Table 4 The interaction effects between unemployment and the number of months in which an individual is already unemployed on *LS* (Models 1 and 2); the interaction effects between anticipated unemployment and the number of months in which an individual is still employed until the first month in unemployment on *LS* (Model 3)

	Ideal patterns	
	(1) *LS*	(2) *LS*
Employment status (M1):		
-30 to -1 (employed)	Ref.	Ref.
0 (becomes unemployed)	-0.663***	-0.736***
Interaction with the number of already existing unemployment months (x9)	-0.0259*	-0.0255*
Anticipation of unemployment (x1):		
no anticipation	-	Ref.
anticipation	-	-0.151***
N	80,029	80,029
R^2	0.045	0.046

	Ideal patterns
	(3) *LS*
Employment status (M1):	
-30 to-2 (employed)	Ref.
-1 (anticipates unemployment)	-0.260***
Interaction with the distance to the first unemployment month (x10)	0.0194**
N	80,029
R^2	0.046

SOEP data; waves a (1984) to bf (2015); own calculation; FE estimations; the within-R^2 and panel robust S.E.s are used; further control variables (*x2*-*x8*), and unemployment years (up to the ninth year in unemployment) have been considered but are not displayed above.

* $p < .05$, ** $p < .01$, *** $p < .001$

If ideal patterns are used, then method *M2* (see *dataset construction and variable operationalization*) can be applied. See Table 5: the *anticipation of unemployment in the next month* (*-0*) is stronger than the anticipation effect in the interval *-1 (-12 to -1)* and the statistically (and in terms of content) insignificant interval *-2 (-24 to -13)*. These findings verify the findings of *H3* and *H5*. The closer that the event is, the greater that the negative *anticipation effect* is. The *immediate reaction effect +0* (the individual is employed in the previous month) is smaller than the effect in the interval *+1 (+1 to +12)*. The reaction effect is not the strongest in the development of the unemployment effect. This difference supports the findings of *H2* and *H4*. The unemployment effect increases at the beginning. See Fig. 4: the development of the unemployment effect (linear function and polynomials up to the fifth degree) is the same as in Table 3 and Model 1.

Table 5 An ideal patterns-based, detailed view of the development of the causal effect of unemployment on *LS* over time: visualized via step and continuous impact functions and anticipation interpreted as the beginning of the development of the unemployment effect

	Ideal patterns (1) *LS*
Employment status (M2):	
employed (-348 to -25)	Ref.
-2 (-24 to -13)	0.0109
-1 (-12 to -1)	-0.131^{***}
-0	-0.408^{***}
+0	-0.674^{***}
+1 (+1 to +12)	-0.821^{***}
+2 (+13 to +24)	-0.848^{***}
+3 (+25 to +36)	-0.786^{***}
+4 (+37 to +48)	-0.859^{***}
+5 (+49 to +60)	-0.813^{***}
+6 (+61 to +72)	-0.779^{***}
+7 (+73 to +84)	-0.664^{***}
+8 (+85 to +96)	-0.605^{**}
+9 (+97 to +108)	-0.705^{**}
Employment status (M2):	
employed (-348 to -13)	Ref.
-1 to -0 (-12 to -0)	-0.160^{***}
The development of the unemployment effect over time:	
Linear function	-1.240^{***}
Quadratic function	0.793^{***}
Cubic function	-0.222^{***}
Fourth-degree polynomial	0.0279^{***}
Fifth-degree polynomial	-0.00128^{**}
N	80,030
R^2	0.046

SOEP data; waves a (1984) to bf (2015); own calculation; FE estimations; the within-R^2 and panel robust S.E.s are used; further control variables (*x2-x8*) have been considered but are not displayed above; the categories -1(-12 to -1) and -0, as well as the categories +0 and +1(+1 to +12), are linked in the analysis of continuous impact functions.

* $p < .05$, ** $p < .01$, *** $p < .001$

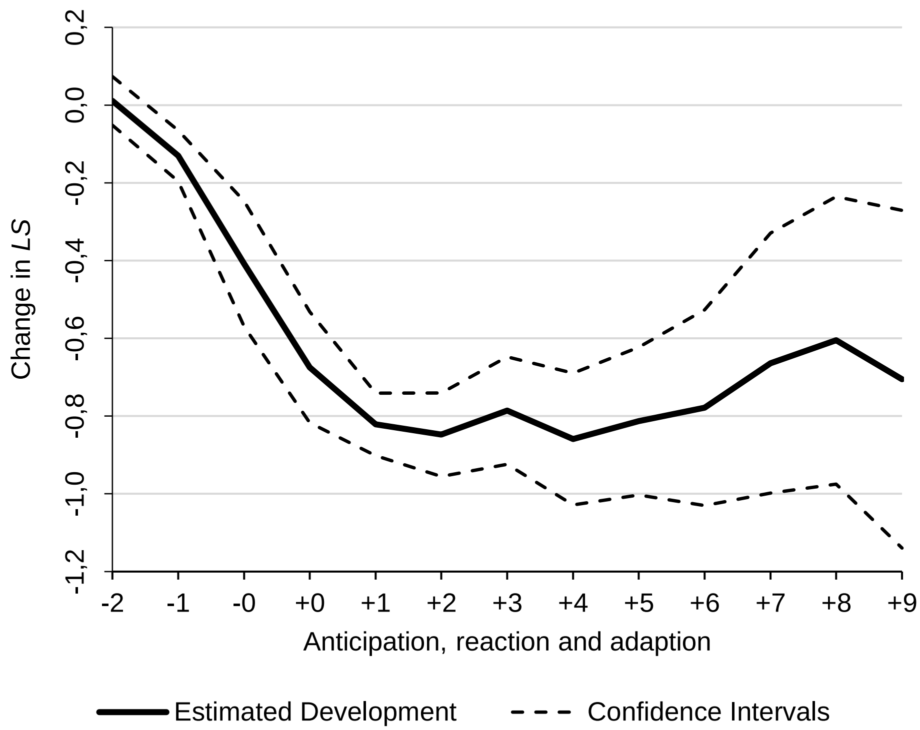


Fig. 4 A more detailed view on the development of the causal effect of unemployment on *LS* over time: Anticipation, reaction and adaption effects if ideal patterns are used. *Note*: SOEP data; waves a (1984) to bf (2015); own illustration; data from Table 5 and Model 1.

See Table 6: the findings remain equal even if the analysis is restricted to the *first observed unemployment period of an individual* where *unemployment experience* as a time-varying confounder is not needed in the analysis model (see Model 1). The findings of this analysis are confronted by an analysis of unemployment periods *only with unemployment experience* (see Model 2) and the *overall analysis* (see Model 3), which can also be viewed in Tables 2 and 3, respectively. There are effects of strength and development differences between the models, but the effect developments up to the fifth year in unemployment seem to be equal. The overall development of the effect is also equal, as the continuous impact functions show. *H2* also applies to Models 1 and 2. See Appendix, Table A11: the more detailed view with *M2* shows that the *anticipation effect*, of those with *no previous unemployment experience*, is not as strong as in Model 2 (only those unemployment periods *with previous unemployment experience*). An interaction effect between *anticipation* and *unemployment experience* shows that the higher the *unemployment experience,* the stronger the *anticipation effect of unemployment* (see Appendix, Table A12).

Table 6 The development of the unemployment effect on *LS* over time: Visualized via step and continuous impact functions, the anticipation interpreted as the beginning of the unemployment effect development and model differentiation by unemployment experience

	Ideal patterns		
	No unemployment experience	Only unemployment experience	With and without unemployment experience
	(1) *LS*	(2) *LS*	(3) *LS*
Employment status (M1):			
-30 to -2 (employed)	Ref.	Ref.	Ref.
-1 (anticipates unemployment)	-0.116**	-0.139***	-0.151***
0 (becomes unemployed)	-0.753***	-0.777***	-0.802***
+1	-0.753***	-0.807***	-0.847***
+2	-0.643***	-0.698***	-0.764***
+3	-0.902***	-0.850***	-0.835***
+4	-0.755***	-0.782***	-0.828***
+5	-0.764***	-0.790***	-0.747***
+6	-0.833***	-0.736***	-0.649***
+7	-0.608	-0.532	-0.543**
+8	-1.027*	-0.886**	-0.710**
Employment status (M1):			
-30 to -2 (employed)	Ref.	Ref.	Ref.
-1 (anticipates unemployment)	-0.117***	-0.139***	-0.152***
The development of the unemployment effect over time:			
Linear function	-1.266***	-1.237***	-1.222***
Quadratic function	0.841***	0.792***	0.749***
Cubic function	-0.237***	-0.217***	-0.200***
Fourth-degree polynomial	0.0291***	0.0263***	0.0238***
Fifth-degree polynomial	-0.00129**	-0.00115***	-0.00103***
N	67,199	69,791	80,029
R^2	0.036	0.040	0.046

SOEP data; waves a (1984) to bf (2015); own calculation; FE estimations; the within-R^2 and panel robust S.E.s are used; further control variables (*x2*-*x8*; in model 1: *x3*-*x8*) have been considered but are not displayed above

* $p < .05$, ** $p < .01$, *** $p < .001$

The second observation is that it seems that substitution will occur earlier if there is no *previous unemployment experience* (see Appendix, Table A11). Nevertheless, the continuous impact functions show that the development of the overall effect remains equal between all models. See Appendix, Table A12: finally, the unemployment effects tend to become smaller as *unemployment experience* increased.

This first interpretation is analysed with interaction effects between the *continuous impact functions* and the *unemployment experience* (see Table 7). The interaction effects of *unemployment experience* with the continuous impact functions are statistically significant except for the interaction with the linear function in Model 2 with method *M2*. Nevertheless, it can be said that the negative effects are smaller as *unemployment experience* increases, and the positive effects become stronger as *unemployment experience* increases.

Table 7 Interactions between the continuous impact functions and the unemployment experience

	Ideal patterns With and without unemployment experience (1) *LS*		*Ideal patterns* With and without unemployment experience (2) *LS*
Employment status (M1):		*Employment status (M2):*	
-30 to -2 (employed)	Ref.	employed (-348 to -13)	Ref.
-1 (anticipates unemployment)	-0.147***	-1 to -0 (-12 to -0)	-0.153***
The development of the unemployment effect over time:		*The development of the unemployment effect over time:*	
Linear function	-1.233***	Linear function	-1.250***
Quadratic function	0.7393***	Quadratic function	0.785***
Cubic function	-0.200***	Cubic function	-0.223***
Fourth-degree polynomial	0.0237***	Fourth-degree polynomial	0.0278**
Fifth-degree polynomial	-0.001***	Fifth-degree polynomial	-0.001**
Interactions with unemployment experience (x2):		*Interactions with unemployment experience (x2):*	
-1 to -0 (-12 to -0)	-0.0064	-1 to -0 (-12 to -0)	-0.0097
Linear function	0.0151*	Linear function	0.01281
Quadratic function	0.0027*	Quadratic function	0.0026*
Cubic function	0.0004*	Cubic function	0.0004*
Fourth-degree polynomial	0.00004*	Fourth-degree polynomial	0.00005*
Fifth-degree polynomial	0.000004*	Fifth-degree polynomial	0.000006*
N	80,029	*N*	80,030
R^2	0.046	R^2	0.046

SOEP data; waves a (1984) to bf (2015); own calculation; FE estimations; the within-R^2 and panel robust S.E.s are used; further control variables (*x3-x8*) have been considered but are not displayed above; the categories -1(-12 to -1) and -0, as well as the categories +0 and +1(+1 to +12), are linked in the analysis of continuous impact functions with *M2*.

* $p < .05$, ** $p < .01$, *** $p < .001$

5 Discussion

As already shown in a previous study (Clark et al. 2008), the first important finding is that *anticipation* must be interpreted as part of the general unemployment effect, particularly as the beginning of the unemployment effect development. Additional tests have also shown that the *anticipation effect* should be especially considered in analyses focusing on unemployment periods *with previous unemployment experiences* because there are stronger *anticipation effects.* Further studies could analyse *mechanism hypotheses,* explaining the *anticipation effects* on *LS*. Are there different mechanisms depending on *unemployment experience,* and do they differ in their effect strengths? The findings for *H2* show that the development of the unemployment effect follows a linear function and polynomials up to the fifth degree. The *reaction effect on unemployment* is not the strongest effect in the unemployment duration. The effect increases at the beginning. This effect development has been described by a linear function. Subsequently, there is an increasing trend in *LS,* which has been described by a quadratic function. Finally, polynomials up to the fifth degree (alternate up and down movements) have identified that the effect of unemployment is persistent over the unemployment duration. According to the SPF theory, it can be interpreted, that the lost resource cannot fully substitute for other resources. In further research, some *mechanism hypotheses* could be analysed that explain the quadratic function or all positive functions. It could be seen that the whole unemployment effect strength decreases over time. Do all positive functions have the same mechanisms or are they differentiated in *substitution effects* (characterized as the mechanism to stop the *LS* decreasing trend at the beginning) and *habituation effects*? Or are they substitution effects with different substitution mechanisms? Some research projects have analysed these substitution effects, especially the effects of working at home and changed leisure activities (Knabe et al. 2010; Esche 2017).

The *modern causal analysis*-oriented successive model construction in *H1* is an indicator of the assumptions about the causal relationships and dynamic outcome development. As shown in previous studies (Brüderl 2010), there is an *LS*-decreasing time trend. In H1, the consideration of *age* and *period effects* decreases the unemployment effect. Therefore, the consideration of time and the control group in the analysis is needed to uncover an apparent correlation. The inclusion of *unemployment experience* increases the unemployment coefficient. This variable is required for the decision that more than one unemployment period of the treatment group individuals is used and for the decision to consider unemployment periods *with previous unemployment experiences.*

The greater that the *unemployment experience* is, the smaller the averaged levels of *LS* (in years of employment and therefore in years of unemployment) are, the stronger the *anticipation effects* are, and the smaller the overall unemployment effects are regarding years in unemployment. The latter development is perhaps an indicator that a *habituation effect* occurs or an indicator that the negative assessment of SWB due to unemployment is not as strong because the reduced SWB baseline in years of employment due to previous unemployment experience (scarring effects of unemployment) is the standard of comparison. The control of *unemployment experience* triggers a suppressor relationship. Controlling for some further events, such as *the birth of a child in the household*, *widowhood*, *marriage* and *divorce*, also triggers suppressor relationships. This trigger also applies to the *anticipation events* in the analysis of the causal effect with non-ideal patterns. The interpretation of *anticipation* as the beginning of the development of the unemployment effect shows that the changed comparison basis (the *anticipation of unemployment* up to one year before becoming unemployed) increases the unemployment coefficient. The inclusion of additional years of employment (as many as possible) is important to support and identify the full effect strength. What are the differences between the analyses with ideal and non-ideal patterns? First, if possible, ideal patterns should be preferred for the analysis. Only ideal patterns should be used for analyses such as the *anticipation of unemployment* (*H3*) and the analysed interactions effects (*H4* and *H5*). The effect differences between ideal and non-ideal patterns are very small by *H1*. If there are many observations, then it is assumed that the ideal patterns will exclude the biased effects of non-ideal patterns. Compared to H2, this outcome applies to the beginning of the unemployment duration. The longer that the unemployment duration is, the smaller the number of observations is per unemployment year, and therefore, the greater the effect differences are between the models with ideal and non-ideal-patterns. If only the direction and form of the unemployment effect development are analysed, then both patterns can be used. A further subsequent research question regards whether there is an *asymmetrical effect of becoming employed after being unemployed*. Do unemployed individuals truly anticipate re-employment and is the development of the re-employment effect over time equal to the development of the unemployment effect?

References

Andreß, H. J., Golsch, K., & Schmidt, A. W. (2013). *Applied panel data analysis for economic and social surveys*. Berlin, Heidelberg: Springer.

Brüderl, J. (2010). Kausalanalyse mit Paneldaten. In C. Wolf & H. Best (Eds.), *Handbuch der sozialwissenschaftlichen Datenanalyse* (pp. 963–994). Wiesbaden: VS Verlag für Sozialwissenschaften.

Clark, A. E., Diener, E., Georgellis, Y., & Richard, E. L. (2008). Lags and leads in life satisfaction: a test of the baseline hypothesis. *The Economic Journal,* 118(529), F222–F243.

Clark, A. E., & Georgellis, Y. (2013). Back to baseline in Britain: adaptation in the British household panel survey. *Economica,* 80(319), 496–512.

Clark, E., Georgellis, Y., & Sanfey, P. (2001). Scarring: the psychological impact of past unemployment. *Economica*, 68(270), 221–241.

Diener, E. (1984). Subjective well-being. *Psychological Bulletin*, 95(3), 542–575.

Esche, F. (2017). *Die folgen der arbeitslosigkeit für partnerschaften*. Wiesbaden: Springer.

Georgellis, Y., Gregoriou, A., Healy, J., & Tsitsianis, N. (2008). Unemployment and life satisfaction: a non-linear adaptation process. *International Journal of Manpower,* 29(7), 668–680.

Goebel, J., Grabka, M. M., Liebig, S., Kroh, M., Richter, D., Schröder, C., & Schupp, J. (2018). The German Socio-Economic Panel (SOEP). Jahrbücher für Nationalökonomie und Statistik/Journal of Economics and Statistics (online first), doi: https://doi.org/10.1515/jbnst-2018-0022.

Goebel, J. (2017). SOEP-core v32 – documentation on biography and life history data. SOEP survey papers, series D–variable descriptions and coding, DIW Berlin, Vol. 418. http://panel.gsoep.de/soep-docs/surveypapers/diw_ssp0418.pdf. Accessed 12 November 2017.

Hahn, E., Specht, J., Gottschling, J., & Frank, M. S. (2015). Coping with unemployment: the impact of unemployment duration and personality on trajectories of life satisfaction. *European Journal of Personality,* 29(6), 635–646.

Hajek, A. (2011). Lebenszufriedenheit und einkommensreichtum: eine empirische analyse mit dem SOEP. SOEP papers on multidisciplinary panel data research, DIW Berlin, Vol. 362. https://www.diw.de/documents/publikationen/73/diw_01.c.369053.de/diw_sp0362.pdf. Accessed 20 April 2018.

Imai, K., & Kim, I. S. (2016). When should we use linear fixed effects regression models for causal inference with longitudinal data? Princeton University: Massachusetts Institute of Technology. from https://imai.princeton.edu/research/files/FEmatch.pdf. Accessed 21 February 2018.

Jahoda, M. (1981). Work, employment, and unemployment: values, theories, and approaches in social research. *American Psychologist,* 36(2), 184–191.

Jahoda, M. (1982). *Employment and unemployment: a social-psychological analysis*. Cambridge, MA: Cambridge University Press.

Jahoda, M., & Brandt, W. (1986). *Wieviel Arbeit braucht der Mensch?: arbeit und arbeitslosigkeit im 20. jahrhundert*. Weinheim, Basel: Beltz Verlag.

Knabe, A., & Rätzel, S. (2011). Scarring or scaring? The psychological impact of past unemployment and future unemployment risk. *Economica,* 78(310), 283–293.

Knabe, A., Rätzel, S., Schöb, R., & Weimann, J. (2010). Dissatisfied with life but having a good day: time-use and well-being of the unemployed. *The Economic Journal,* 120(547), 867–889.

Kühnel, S., & Krebs, D. (2014). *Statistik für die Sozialwissenschaften: grundlagen, Methoden, Anwendungen*. Reinbek bei Hamburg: Rowohlt Taschenbuch Verlag.

Lucas, R. E., Clark, A. E., Georgellis, Y., & Diener, E. (2004). Unemployment alters the set point for life satisfaction. *Psychological Science,* 15(1), 8–13.

Morgan, S. L., & Winship, C. (2015). *Counterfactuals and causal inference: methods and principles for social research*. New York, NY: Cambridge University Press.

O'Donnell, A. T., Corrigan, F., & Gallagher, S. (2015). The impact of anticipated stigma on psychological and physical health problems in the unemployed group. *Frontiers in Psychology,* 6, 1263.

Oesch, D., & Lipps, O. (2011). Does unemployment hurt less if there is more of it around? A panel analysis of life satisfaction in germany and switzerland. (SOEP papers on multidisciplinary panel data research, DIW Berlin, Vol. 393). https://www.diw.de/documents/publikationen/73/diw_01.c.377429.de/diw_sp0393.pdf. Accessed 20 April 2018.

Pearl, J. (2013). *Causality: models, reasoning, and inference*. New York, NY: Cambridge University Press.

Schupp, J., Goebel, J., Kroh, M., Schröder, C., Bartels, C., Erhardt, K., et al. (2017). *Socio-economic panel (SOEP), data from 1984-2015*. SOEP. doi:10.5684/soep.v32.

Uglanova, E. A., & Staudinger, U. M. (2013). Zooming in on life events: is hedonic adaptation sensitive to the temporal distance from the event? *Social Indicators Research*, 111(1), 265–286.

Vaisey, S., & Miles, A. (2016). What you can—and can't—do with three-wave panel data. *Sociological Methods & Research*, 46(1), 44–67.

Veenhoven, R. (2008). Sociological theories of subjective well-being. In M. Eid & R. Larsen (Eds.), *The science of subjective well-being: a tribute to Ed Diener* (pp. 44–61). New York, NY: Guilford Publications.

von Scheve, C., Esche, F., & Schupp, J. (2017). The emotional timeline of unemployment: anticipation, reaction, and adaptation. *Journal of Happiness Studies,* 18(4), 1231–1254.

Wagner, G. G. (2007). Wie die 11er-Skala in das SOEP kam - ein beitrag zu den problemen und möglichkeiten multidisziplinärer forschung und zugleich eine fußnote zum design der SOEP-stichprobe. In J. Schwarze, J. Räbinger & R. Thiede (Eds.), *Arbeitsmarkt- und sozialpolitikforschung im wandel: festschrift für christof helberger zum 65. geburtstag* (pp. 40–62). Hamburg: Kovac.

Winkelmann, L., & Winkelmann, R. (1998). Why are the unemployed so unhappy? Evidence from panel data. *Economica,* 65(257), 1–15.

Wooldridge, J. M. (2010). *Econometric analysis of cross section and panel data*. Cambridge, MA: MIT Press.

Wooldridge, J. M. (2016). *Introductory econometrics: a modern approach*. Boston, MA: Cengage Learning.

Appendix

I Tables

Table A1 Plausibility check and priority assignment of the employment status in each calendar month (Esche 2017)

Employment status		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
(1)	Maternity leave	**B**	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
(2)	Pension		**B**	**X**	**X**	**X**	**X**	**X**	✓	✓	✓	✓	✓
(3)	Civil or military service			**B**	**X**	**X**	**X**	**X**	✓	✓	✓	✓	✓
(4)	Registered unemployed				**B**	✓	✓	**X**	✓	✓	✓	✓	✓
(5)	Initial training					**B**	✓	✓	✓	✓	✓	✓	✓
(6)	School/university						**B**	**X**	✓	✓	✓	✓	✓
(7)	Full-time employed							**B**	✓	✓	✓	✓	✓
(8)	Marginal/part-time employment								**B**	✓	✓	✓	✓
(9)	Other									**B**	✓	✓	✓
(10)	Housework										**B**	✓	✓
(11)	In-company advanced training											**B**	✓
(12)	Short-time work												**B**

Table A2 The episode patterns for the control and experimental group (own illustration)

Control group													
Episode	*Survey year*	*m1*	*m2*	*m3*	*m4*	*m5*	*m6*	*m7*	*m8*	*m9*	*m10*	*m11*	*m12*
1	2000	0	0	0	0	0	0	0	0	0	0	0	0
1	2001	0	0	0	0	0	0	0	0	0	0	0	0
1	2002	0	0	0	0	0	0	0	0	0	0	0	0
1	2003	0	0	0	0	0	0	0	0	0	0	0	0
1	2004	0	0	0	0	0	0	0	0	0	0	0	0

Experimental group													
Episode	*Survey year*	*m1*	*m2*	*m3*	*m4*	*m5*	*m6*	*m7*	*m8*	*m9*	*m10*	*m11*	*m12*
1	2000	0	0	0	0	0	0	0	0	0	0	0	0
1	2001	0	0	0	0	0	0	0	1	1	1	1	1
1	2002	1	1	1	1	1	1	1	1	1	1	1	1
1	2003	1	1	1	1	1	1	1	1	1	1	0	0
2	2004	0	0	0	0	0	0	0	0	0	1	1	1
2	2005	1	1	1	1	1	1	1	1	1	1	1	1
2	2006	1	1	1	1	1	1	1	1	0	0	0	0

Table A3 Identification of similar period effects

	(1)
	LS
Periods:	
1984	Ref.
1985	-0.283***
1986	-0.244***
1987	-0.465***
1988	-0.476***
1989	-0.498***
1990	-0.300***
1991	-0.334***
1992	-0.448***
1993	-0.621***
1994	-0.595***
1995	-0.577***
1996	-0.617***
1997	-0.757***
1998	-0.636***
1999	-0.543***
2000	-0.504***
2001	-0.510***
2002	-0.654***
2003	-0.788***
2004	-0.941***
2005	-0.860***
2006	-0.907***
2007	-0.854***
2008	-0.824***
2009	-0.971***
2010	-0.731***
2011	-0.716***
2012	-0.730***
2013	-0.658***
2014	-0.704***
_cons	7.735***
N	84,650

SOEP data; waves a (1984) to bf (2015); own calculation; RE-estimations

* $p < .05$, ** $p < .01$, *** $p < .001$

Table A4 The description of metric or quasi-metric variables

Serial number			Treatment group: *Non-ideal patterns*	Treatment group: *Ideal patterns*	Control group	Total: *Non-ideal patterns*	Total: *Ideal patterns*
1	How many spells do individuals have?	Obs	4455	3705	7342	11,797	11,047
		Mean	7.273625	7.106073	7.085808	7.156735	7.092604
		Std. Dev.	5.284273	5.254416	5.540405	5.445631	5.445933
		Min	2	2	2	2	2
		Max	31	31	31	31	31
2	The age of the individuals	Obs	32,404	28,126	52,024	84,428	80,150
		Mean	42.91137	43.38537	43.58919	43.32904	43.51767
		Std. Dev.	11.28533	11.23279	9.113867	10.00855	9.909578
		Min	18	18	18	18	18
		Max	64	64	64	64	64
3	The *LS* of the individuals	Obs	32,404	28,126	52,024	84,428	80,150
		Mean	6.406771	6.439273	7.482431	7.069586	7.116369
		Std. Dev.	1.941665	1.930433	1.494455	1.759768	1.733551
		Min	0	0	0	0	0
		Max	10	10	10	10	10
4	How many spells do individuals have overall unemployment periods?	Obs	5730	4727	-	-	-
		Mean	5.655148	5.551301	-	-	-
		Std. Dev.	4.319468	4.36223	-	-	-
		Min	2	2	-	-	-
		Max	31	31	-	-	-
5	The *LS* of individuals in the years of employment	Obs	21,370	18,700	-	-	-
		Mean	6.753112	6.783529	-	-	-
		Std. Dev.	1.782888	1.766244	-	-	-
		Min	0	0	-	-	-
		Max	10	10	-	-	-
6	The *LS* of individuals in the years of unemployment	Obs	11,034	9426	-	-	-
		Mean	5.735998	5.756312	-	-	-
		Std. Dev.	2.057542	2.05658	-	-	-
		Min	0	0	-	-	-
		Max	10	10	-	-	-
7	How much unemployment experience do the individuals have?	Obs	4455	3899	-	-	-
		Mean	2.247587	2.06258	-	-	-
		Std. Dev.	1.624901	1.42314	-	-	-
		Min	1	1	-	-	-
		Max	15	13	-	-	-
8	For how many months are the individuals already unemployed at the start of unemployment (h1=31)?	Obs	-	5428	-	-	-
		Mean	-	4.683125	-	-	-
		Std. Dev.	-	3.615095	-	-	-
		Min	-	0	-	-	-
		Max[a]	-	17	-	-	-

[a] If all years in unemployment are considered, then the maximal duration is 202 months.

Table A4 (continued)

Serial number			Treatment group: *Non-ideal patterns*	Treatment group: *Ideal patterns*
9	For how many months from the last interview month in employment (h1=30) until the first unemployment month are the individuals employed?	Obs	-	5428
		Mean	-	6.158806
		Std. Dev.	-	3.618002
		Min	-	0
		Max[b]	-	18
10	*LS*; *h1*= -30 to -1; *x2*=0	Mean	-	6.960584
	LS; *h1*= -30 to -1; *x2*=1	Mean	-	6.638588
	LS; *h1*= -30 to -1; *x2*=2	Mean	-	6.535611
	LS; *h1*= -30 to -1; *x2*=3	Mean	-	6.206349
	LS; *h1*= -30 to -1; *x2*=4	Mean	-	6.3
	LS; *h1*= -30 to -1; *x2*=5	Mean	-	6.152047
	LS; *h1*= -30 to -1; *x2*=6	Mean	-	6.3
11	*LS*; *h1*= 0 to +16; *x2*=1	Mean	-	5.974508
	LS; *h1*= 0 to +16; *x2*=2	Mean	-	5.676017
	LS; *h1*= 0 to +16; *x2*=3	Mean	-	5.603788
	LS; *h1*= 0 to +16; *x2*=4	Mean	-	5.33758
	LS; *h1*= 0 to +16; *x2*=5	Mean	-	5.545882
	LS; *h1*= 0 to +16; *x2*=6	Mean	-	5.598802
	LS; *h1*= 0 to +16; *x2*=7	Mean	-	5.5

SOEP data; waves a (1984) to bf (2015); own calculation

[b] If all years in employment are considered, then the maximal duration is 345 months.

Table A5 The description of the employment and unemployment years with the methods *M1* and *M2*

	Treatment group	
	Non-ideal patterns	*Ideal patterns*
M1	Freq.	Freq.
-30	3	1
-29	3	2
-28	5	4
-27	6	5
-26	7	5
-25	7	5
-24	14	12
-23	14	12
-22	25	23
-21	36	32
-20	48	42
-19	67	55
-18	84	69
-17	109	94
-16	129	111
-15	165	145
-14	205	181
-13	257	226
-12	312	271
-11	406	356
-10	526	456
-9	649	561
-8	792	686
-7	961	830
-6	1187	1016
-5	1478	1249
-4	1927	1608
-3	2591	2160
-2	3627	3055
-1	5730	5428
0	5730	5428
+1	2329	1832
+2	1127	857
+3	624	454
+4	412	297
+5	260	177
+6	179	121
+7	115	77
+8	89	62
+9	60	42
+10	43	32
+11	25	19
+12	15	11
+13	11	8
+14	6	4
+15	5	3
+16	4	2
Total	32,404	28,126

SOEP data; waves a (1984) to bf (2015); own calculation

	Treatment group
	Ideal patterns
M2	Freq.
-29 (-348 to -337)	2
-28 (-336 to -325)	4
-27 (-324 to -313)	5
-26 (-312 to -301)	5
-25 (-300 to -289)	5
-24 (-288 to -277)	12
-23 (-276 to -265)	13
-22 (-264 to -253)	22
-21 (-252 to -241)	29
-20 (-240 to -229)	43
-19 (-228 to -217)	55
-18 (-216 to -205)	71
-17 (-204 to -193)	88
-16 (-192 to -181)	110
-15 (-180 to -169)	137
-14 (-168 to -157)	183
-13 (-156 to -145)	220
-12 (-144 to -133)	267
-11 (-132 to -121)	350
-10 (-120 to -109)	445
-9 (-108 to -97)	545
-8 (-96 to -85)	686
-7 (-84 to -73)	828
-6 (-72 to -61)	1016
-5 (-60 to -49)	1219
-4 (-48 to -37)	1566
-3 (-36 to -25)	2088
-2 (-24 to -13)	3024
-1 (-12 to -1)	5165
-0	497
+0	595
+1 (+1 to +12)	4978
+2 (+13 to +24)	1740
+3 (+25 to +36)	830
+4 (+37 to +48)	440
+5 (+49 to +60)	291
+6 (+61 to +72)	170
+7 (+73 to +84)	122
+8 (+85 to +96)	78
+9 (+97 to +108)	62
+10 (+109 to +120)	45
+11 (+121 to +132)	29
+13 (+133 to +144)	18
+14 (+145 to +156)	11
+15 (+157 to +168)	8
+16 (+169 to +180)	4
+17 (+181 to +192)	3
+18 (+193 to +204)	2
Total	28,126

Table A6 Descriptive statistics of nominal and ordinal scaled variables

Serial number			Treatment group				Control group		Total			
			Non-ideal patterns		*Ideal patterns*				*Non-ideal patterns*		*Ideal patterns*	
			Freq.	Percent	Freq.	Percent	Freq.	Percent	Freq.	Percent	Freq.	Percent
1	How many person-years are in the dataset?	0-no	21,370	65.95	18,700	66.49	52,024	100.00	73,394	86.93	70,724	88.24
		1-yes	11,034	34.05	9426	33.51	-	-	11,034	13.07	9426	11.76
		Total	32,404	100.00	28,126	100.00	52,024	100.00	84,428	100.00	80,150	100.00
2	How many individuals are in the dataset?	Total	4455	-	3705	-	7342	-	11,797	-	11,047	-
3	How many widowhood events are in the dataset?	0-no	32,380	99.93	28,102	99.91	51,990	99.93	84,370	99.93	80,092	99.93
		1-yes	24	0.07	24	0.09	34	0.07	58	0.07	58	0.07
		Total	32,404	100.00	28,126	100.00	52,024	100.00	84,428	100.00	80,150	100.00
4	How many divorce-events are in the dataset?	0-no	32,184	99.32	27,937	99.33	51,733	99.44	83,917	99.39	79,670	99.40
		1-yes	220	0.68	189	0.67	291	0.56	511	0.61	480	0.60
		Total	32,404	100.00	28,126	100.00	52,024	100.00	84,428	100.00	80,150	100.00
5	How many marriage-events are in the dataset?	0-no	31,952	98.61	27,739	98.62	51,335	98.68	83,287	98.65	79,047	98.66
		1-yes	452	1.39	387	1.38	689	1.32	1141	1.35	1076	1.34
		Total	32,404	100.00	28,126	100.00	52,024	100.00	84,428	100.00	80,150	100.00
6	How many childbirth events are in the dataset?	0-no	31,675	97.75	27,522	97.66	50,807	97.66	82,482	97.70	78,329	97.73
		1-yes	729	2.25	604	2.34	1217	2.34	1946	2.30	1821	2.27
		Total	32,404	100.00	28,126	100.00	52,024	100.00	84,428	100.00	80,150	100.00
7	How many unemployment- anticipation-events are in the dataset?	0-no	25,978	80.17	22,698	80.70	-	-	-	-	-	-
		1-yes	6426	19.83	5428	19.30	-	-	-	-	-	-
		Total	32,404	100.00	28,126	100.00	-	-	-	-	-	-

Table A6 (continued)

Serial number			Treatment group				Control group		Total			
			Non-ideal patterns		*Ideal patterns*				*Non-ideal patterns*		*Ideal patterns*	
			Freq.	Percent	Freq.	Percent	Freq.	Percent	Freq.	Percent	Freq.	Percent
8	How many unemployment periods do individuals in the treatment group have?	1	3504	78.65	2989	80.67	7342	100.00	10,846	91.94	10,331	93.52
		2	687	15.42	535	14.44	-	-	687	5.82	535	4.84
		3	208	4.67	144	3.89	-	-	208	1.76	144	1.30
		4	54	1.21	36	0.97	-	-	54	0.46	36	0.33
		5	1	0.02	0	0.00	-	-	1	0.01	0	0.00
		6	0	0.00	0	0.00	-	-	0	0.00	0	0.00
		7	1	0.02	1	0.03	-	-	1	0.01	1	0.01
		Total	4455	100.00	3705	100.00	7342	100.00	11,797	100.00	11,047	100.00

SOEP data; waves a (1984) to bf (2015); own calculation

Table A7 Description of the survey year distribution

	Treatment group		Control group	Total	
	Non-ideal patterns	*Ideal patterns*		*Non-ideal patterns*	*Ideal patterns*
	Freq.	Freq.	Freq.	Freq.	Freq.
1984	626	554	1301	1927	1855
1985	691	622	1322	2013	1944
1986	705	631	1180	1885	1811
1987	696	633	1026	1722	1659
1988	683	612	884	1567	1496
1989	661	588	794	1455	1382
1990	659	595	748	1407	1343
1991	1097	978	704	1801	1682
1992	1276	1127	662	1938	1789
1993	1353	1194	609	1962	1803
1994	1399	1229	641	2040	1870
1995	1390	1227	677	2067	1904
1996	1359	1203	678	2037	1881
1997	1313	1131	623	1936	1754
1998	1337	1147	876	2213	2023
1999	1269	1097	875	2144	1972
2000	1621	1377	2399	4020	3776
2001	1655	1417	2400	4055	3817
2002	1697	1474	2776	4473	4250
2003	1623	1400	2663	4286	4063
2004	1491	1289	2479	3970	3768
2005	1303	1123	2293	3596	3416
2006	1177	995	2480	3657	3475
2007	1042	868	2315	3357	3183
2008	926	779	2086	3012	2865
2009	774	651	1915	2689	2566
2010	690	567	2489	3179	3056
2011	594	505	2694	3288	3199
2012	551	474	3208	3759	3682
2013	455	396	3244	3699	3640
2014	291	243	2983	3274	3226
Total	32,404	28,126	52,024	84,428	80,150

SOEP data; waves a (1984) to bf (2015); own calculation

Table A8 Is there sufficient within-variation on the variables?

Variables		**Treatment group** *Non-ideal patterns*	*Ideal patterns*	**Control group**	**Total** *Non-ideal patterns*	*Ideal patterns*
Unemployment	Std. Dev.	0.4204509	0.4193556	0	0.2604757	0.248416
Age	Std. Dev.	3.867512	3.732427	3.882171	3.876528	3.830267
Unemployment experience	Std. Dev.	0.9101213	0.7348688	0	0.5638339	0.4353184
Widowhood	Std. Dev.	0.0255909	0.0274471	0.0240575	0.0246571	0.0252986
Divorce	Std. Dev.	0.0763026	0.0754693	0.0697498	0.0723346	0.0718083
Marriage	Std. Dev.	0.1083776	0.1061368	0.1065043	0.1072265	0.1063748
Birth of a child	Std. Dev.	0.1329098	0.1276644	0.1372175	0.1355796	0.133942
Anticipation of unemployment	Std. Dev.	0.3768239	0.3727162	0	0.2334481	0.220788
	Total (N)	32,404	28,126	52,024	84,428	80,150

SOEP data; waves a (1984) to bf (2015); own calculation; the within Std. Dev. is used

Table A9 The development of the causal effect of unemployment on *LS* over time: Visualized as step impact function

	Ideal patterns		*Non-ideal patterns*	
	(1) *LS*	(2) *LS*	(3) *LS*	(4) *LS*
Employment status (M1):				
-30 to -1 (employed)	Ref.	Ref.	Ref.	Ref.
0 (become unemployed)	-0.731***	-0.804***	-0.718***	-0.792***
+1	-0.781***	-0.849***	-0.758***	-0.830***
+2	-0.698***	-0.766***	-0.699***	-0.771***
+3	-0.767***	-0.838***	-0.763***	-0.839***
+4	-0.760***	-0.832***	-0.719***	-0.796***
+5	-0.677***	-0.750***	-0.703***	-0.782***
+6	-0.580***	-0.655***	-0.593***	-0.674***
+7	-0.470*	-0.547**	-0.366*	-0.448**
+8	-0.641**	-0.719**	-0.557**	-0.641**
+9	-0.274	-0.353	-0.602*	-0.688**
+10	-0.570*	-0.651*	-0.492	-0.580*
+11	-0.788*	-0.871*	-0.530	-0.620
+12	-0.190	-0.276	-0.215	-0.307
+13	-0.199	-0.284	-0.00607	-0.0982
+14	-0.355	-0.445	0.204	0.107
+15	-0.671	-0.761	-1.297	-1.394
+16	-1.024***	-1.123***	-0.586	-0.689
Anticipation of unemployment (x1):				
no anticipation	-	Ref.	-	Ref.
anticipation	-	-0.152***	-	-0.159***
N	80,150	80,150	84,428	84,428
R^2	0.045	0.046	0.046	0.047

SOEP data; waves a (1984) to bf (2015); own calculation; FE-estimations; the within-R^2 and panel robust S.E.s are used; further control variables (*x2-x8*) have been considered but are not displayed above

* $p < .05$, ** $p < .01$, *** $p < .001$

Table A10 The anticipation of unemployment regarding the *LS*

	Ideal patterns (1) *LS*
Employment status (M1):	
-30 to -3 (employed)	Ref.
-2 (anticipate unemployment)	0.00327
-1 (anticipate unemployment)	-0.150***
N	80,029
R^2	0.046

SOEP data; waves a (1984) to bf (2015); own calculation; FE-estimations; the within-R^2 and panel robust S.E.s are used; further control variables (*x2*-*x8*) and unemployment years (up to the ninth year in unemployment) have been considered but are not displayed above

* $p < .05$, ** $p < .01$, *** $p < .001$

Table A11 An ideal patterns-based, detailed view of the development of the causal effect of unemployment on *LS* over time: visualized via step and continuous impact functions, the anticipation interpreted as the beginning of the unemployment effect development and a model differentiation by unemployment experience

	Ideal patterns		
	No unemployment experience	Only with unemployment experience	With and without unemployment experience
	(1)	(2)	(3)
	LS	*LS*	*LS*
Employment status (M2):			
employed (-348 to -13)	Ref.	Ref.	Ref.
-1 (-12 to -1)	-0.102**	-0.130***	-0.135***
-0	-0.347*	-0.358***	-0.412***
+0	-0.639***	-0.667***	-0.678***
+1 (+1 to +12)	-0.771***	-0.792***	-0.825***
+2 (+13 to +24)	-0.759***	-0.832***	-0.851***
+3 (+25 to +36)	-0.614***	-0.703***	-0.790***
+4 (+37 to +48)	-0.982***	-0.927***	-0.863***
+5 (+49 to +60)	-0.746***	-0.763***	-0.817***
+6 (+61 to +72)	-0.767***	-0.816***	-0.783***
+7 (+73 to +84)	-0.796**	-0.697***	-0.668***
+8 (+85 to +96)	-0.806*	-0.730**	-0.609**
+9 (+97 to +108)	-0.971*	-0.909**	-0.710**
N	67,200	69,791	80,030
R^2	0.037	0.040	0.046
Employment status (M2):			
employed (-348 to -13)	Ref.	Ref.	Ref.
-1 to -0 (-12 to -0)	-0.124**	-0.152***	-0.160***
The development of the unemployment effect over time:			
Linear function	-1.336***	-1.221***	-1.240***
Quadratic function	0.960***	0.801***	0.793***
Cubic function	-0.293***	-0.230***	-0.222***
Fourth degree polynomial	0.0391**	0.0294**	0.0279***
Fifth degree polynomial	-0.00188**	-0.00137*	-0.00128**
N	67,200	69,791	80,030
R^2	0.037	0.040	0.045

SOEP data; waves a (1984) to bf (2015); own calculation; FE-estimations; the within-R^2 and panel robust S.E.s are used; further control variables (*x2-x8*; in model 1: *x3-x8*) have been considered but are not displayed above; the categories -1(-12 to -1) and -0, as well as the categories +0 and +1(+1 to +12), are linked in the analysis of continuous impact functions.

* $p < .05$, ** $p < .01$, *** $p < .001$

Table A12 Interactions between the step impact functions and the unemployment experience

	Ideal patterns
	With and without unemployment experience (1) *LS*
Employment status (M2):	
employed (-348 to -13)	Ref.
-1 (-12 to -1)	-0.096**
-0	-0.423***
+0	-0.686***
+1 (+1 to +12)	-0.869***
+2 (+13 to +24)	-0.837***
+3 (+25 to +36)	-0.575***
+4 (+37 to +48)	-1.123***
+5 (+49 to +60)	-0.907***
+6 (+61 to +72)	-0.878***
+7 (+73 to +84)	-0.872**
+8 (+85 to +96)	-1.018**
+9 (+97 to +108)	-1.101**
Interactions with unemployment experience (x2):	
-1 (-12 to -1)	-0.0382*
-0	0.0086
+0	0.0038
+1 (+1 to +12)	0.0251
+2 (+13 to +24)	-0.0073
+3 (+25 to +36)	-0.103**
+4 (+37 to +48)	0.1144*
+5 (+49 to +60)	0.0386
+6 (+61 to +72)	0.0407
+7 (+73 to +84)	0.0879
+8 (+85 to +96)	0.1733*
+9 (+97 to +108)	0.1637
N	80,030
R^2	0.046

SOEP data; waves a (1984) to bf (2015); own calculation; FE-estimations; the within-R^2 and panel robust S.E.s are used; further control variables (*x3-x8*) have been considered but are not displayed above

* $p < .05$, ** $p < .01$, *** $p < .001$

II Figures

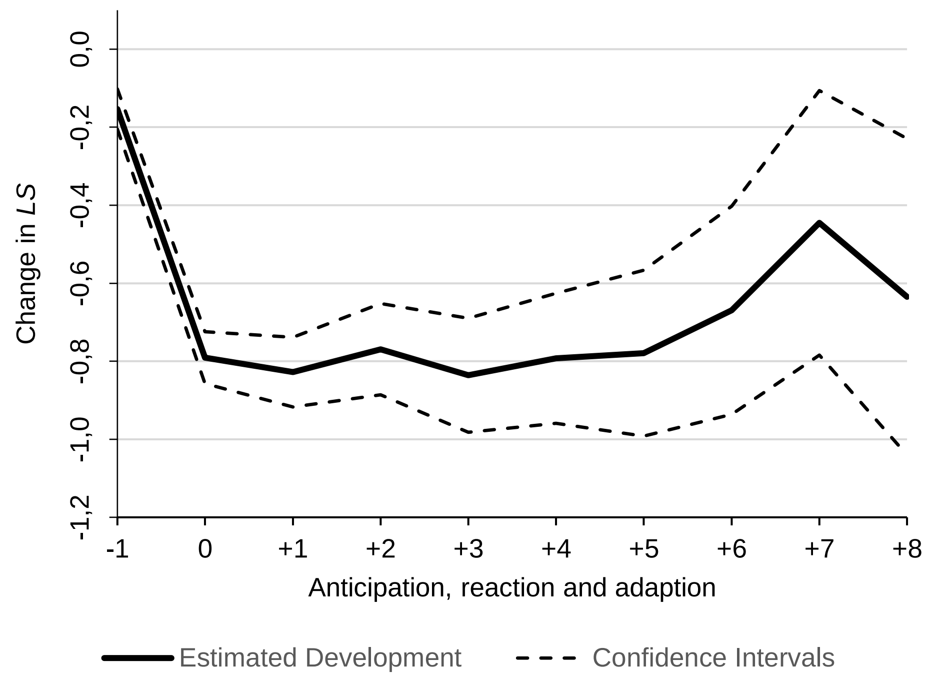


Fig. A1 The development of the causal effect of unemployment on *LS* over time: Anticipation, reaction and adaption effects if non-ideal patterns are used. *Note*: SOEP data; waves a (1984) to bf (2015); own illustration; data of Table 2 and Model 3