sociological science

There's More in the Data! Using Month-Specific Information to Estimate Changes Before and After Major Life Events

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Abstract: Sociological research is increasingly using survey panel data to examine changes in diverse outcomes over life course events. Most of these studies have one striking similarity: they analyze changes between yearly time intervals. In this article, we present a simple but effective method to model such trajectories more precisely using available data. The approach exploits month-specific information regarding interview and life event dates. Using fixed effects regression models, we calculate monthly dummy estimates around life events and then run nonparametric smoothing to create smoothed monthly estimates. We test the approach using Monte Carlo simulations and Socio-economic Panel (SOEP) data. Monte Carlo simulations show that the newly proposed smoothed monthly estimates outperform yearly dummy estimates, especially when there is rapid change or discontinuities in trends at the event. In the real data analyses, the novel approach reports an amplitude of change that is roughly twice as large as the yearly estimates showed. It also reveals a discontinuity in trajectories at bereavement, but not at childbirth; and remarkable gender differences. Our proposed method can be applied to several available data sets and a variety of outcomes and life events. Thus, for research on changes around life events, it serves as a powerful new tool in the researcher's toolbox.

Keywords: panel data; life events; fixed effects regression; panel regression; life satisfaction

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WHEN researchers want to find out how life events affect people and how their satisfaction, health, or earnings change when they marry, become parents, or lose their jobs, they analyze panel data (e.g., Leopold, Leopold, and Lechner 2017; Ludwig and Brüderl 2018; Meadows, McLanahan, and Brooks-Gunn 2008; Musick, Bea, and Gonalons-Pons 2020; Myrskylä and Margolis 2014). With such data, researchers can not only compare between people who have experienced an event and those who have not, but they can also trace changes within the same individuals over time (e.g., Halaby 2004). Beginning 50 years ago with the Panel Study of Income Dynamics (Pfeffer, Fomby, and Insolera 2020), long-term panel surveys, which collect information about the same individuals over many years, became available in several countries and were harmonized for comparative analyses (most recently: "The Comparative Panel File CPF," Turek and Leopold 2021). Conducting panel data studies on changes in outcomes before and after a life event is a thriving field of social science research (most recently, e.g., Mari and Cutuli 2021; Nylin et al. 2021; Schulz and Raab 2022; Torche and Rauf 2021; Tosi and Goisis 2021; Van Winkle and Leopold 2021). Therefore, any methodological innovation that can be applied to such analyses will have vast applications.

When Halaby published a review on panel data studies in sociology in 2004, fixed effects regression analyses were still relatively rare, but they have since become the workhorse in panel survey based research on life events. Most of these studies have one striking similarity: they analyze changes between *yearly* time intervals before and after the event. This might be attributed to the most common schedule of large-scale panel studies—annual waves—making yearly dummies the seemingly natural choice. However, comparing between yearly intervals might not be appropriate because changes can occur over much shorter periods of time (cf. Huinink and Brüderl 2021). Indeed, the currently most common approach might underestimate the amplitude of change, overlook discontinuities at life events, or generally misrepresent the shape of trends.

A straightforward remedy for this could be to implement more fine-grained survey designs, such as monthly panel waves (e.g., Lazarsfeld, Berelson, and Gaudet 1940) or more frequent survey measurements via mobile phones (e.g., Jäckle et al. 2019; Toepoel, Lugtig, and Schouten 2020). However, this form of data collection is expensive and burdensome to respondents (e.g., Barber et al. 2016); it is therefore mainly restricted to specific populations (e.g., young women at risk of unintended pregnancies, Barber, Kusunoki, and Gatny 2011) and/or particular, shorter periods such as the months around elections (DeBell, Krosnick, and Lupia 2010; GLES 2021) or those after the outbreak of the COVID-19 pandemic (Burton, Lynn, and Benzeval 2020; Haas et al. 2021).

Our aim is not to call for the collection of more high-frequency panel surveys but to leverage all of the information that is already available in many annual panel data studies. We introduce a method to describe and analyze the effects of major life events on individual outcomes in more detail. In many panel studies, both the month-specific dates of life events and interviews are reported. In this article, we present an analytical approach to analyze fine-grained trajectories around major life events. Using fixed effects regression models, we calculate monthly dummy estimates around life events and then run nonparametric smoothing to create smoothed monthly estimates. The currently common practice in life events research using survey panel studies is to calculate yearly dummy-estimates. Our approach adds two innovations to this practice. First, we use the full monthly information, which were discarded by previous studies on life events using survey panel data. Second, we propose a smoothing-approach that allows to estimate flexible, continuous trajectories without prior assumptions on their functional form, while avoiding noisy estimates.

In this article, we first compare the performance of our proposed method to the current state of the art of yearly dummy estimates using Monte Carlo simulations. Second, we apply the new method to two different life events—childbirth and bereavement—and determine the extent to which life satisfaction changes in the three years before and after these events. We use the annual waves from the German Socio-economic Panel (SOEP) to show that the *smoothed monthly estimates* approach provides a more precise and complete picture of changes in life satisfaction around these life events. Specifically, we find that (1) the change in satisfaction occurs faster and with an amplitude up to twice as great than is suggested by yearly dummy estimates; (2) gender differences in trajectories are greater than previously assumed;

(3) there is a markable discontinuity in the satisfaction-trend at bereavement but not at the birth of the first child. These new insights substantiate our central claim: "There's more in the data."

The methods that researchers have available in their toolbox determine how they approach research problems and which research problems they tackle in the first place. This is called the Law of the Instrument, perhaps best exemplified by Kaplan ([1964] 1998:28): "Give a small boy a hammer, and he will find that everything he encounters needs pounding." Less famous but just as relevant is the flipside of this: a boy or girl trained in using that hammer will search and pound the remotest nail but ignore the loose screw in plain sight. Kaplan describes how this pattern applies to research: "[. . .] a scientist formulates problems in a way which requires for their solution just those techniques in which he himself is especially skilled" (Kaplan [1964] 1998:28). Available methods affect which research questions are asked and which hypotheses are developed. The possibility of studying trajectories in more temporal detail—a new tool in the toolbox—may thus stimulate more theoretical and empirical considerations of the timing and magnitude of how individuals anticipate and adapt to immediate changes in response to life events, as well as the extent of short- and long-term changes. Hence, the article may more generally contribute to theorizing about and estimating how and through which mechanisms life events impact individual outcomes.

Literature Review

Numerous studies in sociology, demography, and economics have used large-scale panel surveys of population samples to analyze the consequences of major life events. Substantively, the interest is often to understand trajectories rather than focus on single coefficients that refer to one specific time point (Miller 2023). The analysis of panel data to study the consequences of specific life events is particularly well-established in the family domain. For example, various studies analyze the impact of childbirth on life satisfaction, the labor market situation, division of housework, or attitudes (Aassve, Luppi, and Mencarini 2021; Baxter et al. 2015; Buchler, Perales, and Baxter 2017; Georgellis, Lange, and Tabvuma 2012; Kratz 2021; Kühhirt 2012; Mari and Cutuli 2021; Musick et al. 2020; Myrskylä and Margolis 2014; Nomaguchi and Milkie 2020; Nylin et al. 2021; Pollmann-Schult 2014; Torche and Rauf 2021; Tosi and Goisis 2021; West et al. 2019). Further studies, meanwhile, deal with other family events, such as dissolution and divorce (Gardner and Oswald 2006; Leopold 2018; Preetz 2022; Tosi and van den Broek 2020; Van Winkle and Leopold 2021), caregiving (Gerlich and Wolbring 2021), separation of parents (Goisis, Özcan, and Van Kerm 2019; Sun and Li 2002), death of parents (Leopold and Lechner 2015; West et al. 2019), or children moving out (Schulz and Raab 2022).

Furthermore, many researchers interested in labor market transitions have used panel data to study—among other factors—job loss, entering self-employment, and retirement, and how these changes are associated with changes in life satisfaction, personality traits, or risk-taking (Anger, Camehl, and Peter 2017; Brüderl, Kratz, and Bauer 2019; Hahn et al. 2015; Hanglberger and Merz 2015; Hetschko, Knabe, and Schöb 2019; Leopold et al. 2017; Lucas et al. 2004; Merz 2018; van der Zwan, Hessels, and Rietveld 2018). Other research has looked at how health, well-being, and wages change over the course of life events, such as migration or moving (Erlinghagen, Kern, and Stein 2021; Nowok, Findlay, and McCollum 2018; Wolbring 2017), the occurrence of disability (Oswald and Powdthavee 2008; Pagán-Rodríguez 2012; Powdthavee 2009), children's incarceration (Sirois 2020), and becoming a volunteer (Eberl and Krug 2021). This overview is by no means exhaustive, but it shows that analyzing panel data to examine outcomes before and after a life event is a thriving field of social science research.

Concerning the analytical approach, in its most simple form, the panel data is analyzed using a *before and after comparison*. For example, Baxter et al. (2015) studied men's and women's attitudes before and after experiencing parenthood using the HILDA panel data. The authors compared (the mean of) all observations before childbirth to (the mean of) all observations after childbirth (while controlling for a number of other variables). More specifically, they ran fixed effects panel regression models where the coefficient of interest was a dummy variable indicating whether the individual was observed before or after the event.

Going beyond a mere dichotomy of observations before and after an event, many studies analyze changes over a series of predefined periods. They assign each period a dummy variable, which allows for the flexible, nonparametric estimation of the trajectory. In fact, the majority of studies analyze changes between *yearly* time points before and after the event—which is why we describe this as the current state of the art and use it as a reference point for our analyses (Aassve et al. 2021; Brüderl et al. 2019; Erlinghagen et al. 2021; Gardner and Oswald 2006; Georgellis et al. 2012; Gerlich and Wolbring 2021; Goisis et al. 2019; Hanglberger and Merz 2015; Hetschko et al. 2019; Kratz 2021; Leopold et al. 2017; Mari and Cutuli 2021; Merz 2018; Musick et al. 2020; Nowok et al. 2018; Nylin et al. 2021; Pagán-Rodríguez 2012; Powdthavee 2009; Preetz 2022; Schulz and Raab 2022; Tosi and van den Broek 2020; Tosi and Goisis 2021; Van Winkle and Leopold 2021; West et al. 2019; Wolbring 2017; van der Zwan et al. 2018). Some studies use intervals that are even broader than yearly intervals or distinguish between time intervals of varying sizes (e.g., Eberl and Krug 2021). They typically use one-year categories close to the event and intervals of two years or longer for periods further away from the event (Leopold 2018; Myrskylä and Margolis 2014; Pollmann-Schult 2014; Torche and Rauf 2021).

A few studies look at shorter observation periods before and after events (Buddelmeyer and Powdthavee 2016; Mervin and Frijters 2014; Schröder and Schmiedeberg 2015). For example, Mervin and Fijters (2014) examined well-being after negative life events and used dummy variables for six-month intervals in the annual panel data. Schröder and Schmiedeberg (2015) analyze frequency of intercourse in couples before and after marriage and childbirth distinguishing between the first and the second half-year after the event (and used yearly or larger time intervals for the periods further away from the event). Buddelmeyer and Powdthavee (2016:20) studied emotional pain after negative life events using yearly dummies in their main analyses and quarterly dummies for robustness checks. Based on these robustness checks, they point out that observations with closer proximity to the event reveal stronger effects. However, they stuck to yearly dummies for the main analyses because the quarterly dummies are based on too few observations in each quarter-group and are therefore noisy. Finally, Lawes et al. (2022) were specifically interested in the immediate effect of unemployment on well-being and estimated month-to-month changes. However, the data they analyzed differed from those of most other studies: they used a high-frequency panel where individuals were indeed interviewed at monthly intervals.

The nonparametric grouping of pre- and post-event periods of observations has been complemented by adding parametric functions of time relative to the event into the model. Leopold and Kalmijn (2016) used a binary before and after comparison of well-being before and after divorce combined with linear and quadratic duration variables to represent the years since the divorce. However, the authors justified these functional forms by referring to models with a set of dummy variables that allowed for year-to-year changes in the effects of divorce (i.e., the approach of predefined observation periods that we have explained above).

Strategies To Identify Changes In Outcomes Surrounding Life Events: State Of The Art And Extensions

Current State of the Art: Yearly Dummy Estimates

The current common approach in research on changes in diverse outcomes surrounding life events is to run regression models with fixed effects at the individual level that estimate "impact dummies" for *predefined observation periods before and after the event*, mostly yearly periods (see the applied literature in the previous section or, for methodological literature, e.g., Andreß, Golsch, and Schmidt 2013; Ludwig and Brüderl 2021). By including fixed effects at the individual level, the models ensure that the estimated trajectories represent changes within individuals and are not contaminated by unobserved between-person heterogeneity (Halaby 2004).

Specifying impact dummies before and after the event enables researchers to adopt a highly flexible approach to estimating change. For example, when one analyzes the period of three years before and after an event, a fixed effects model for i = 1, . . . n individuals using yearly dummies can be specified as follows:

Individual-level fixed effects

Dummy for the period two years (24 to 12 months) before the event (third year before event is the reference category / omitted)

$$y_{it} = \alpha + \alpha_i + \beta 1_{year\,-2} + \beta 2_{year\,-1} + \ldots + \beta 5_{year\,+3} + u_{it} \qquad (1)$$

Constant

Time-varying error term

The model provides an estimated dummy variable for each year group. For an observation window of three years in both directions of the event, the model estimates a constant (α) as a reference category, plus five coefficients ($\beta 1$–$\beta 5$). $\beta 1$

estimates the difference in the outcome relative to the reference category (the third year before the event) for all observations that occur in the second year before the event (i.e., between 24 and 13 months before the event). $\beta 2$ estimates the difference between the reference category and the year before the event, and so forth. The model thereby averages over all observations that fall into a 12-month period, which may obscure relevant short-term variations and potential peaks near the occurrence of the event.

First Extension to the State of the Art: Monthly Dummy Estimates

Think of a typical panel survey with annual interviews and two interviews that surround a life event. Many panel data sets contain month-specific information about the date of the interviews and specific life events, and, thereby, how many months lie between an interview and an event—information that is often discarded. However, this information could easily be used to describe monthly changes to the outcome before and after the event and analyze anticipation, peaks, and adaptation in greater detail than before.

Given the available data, the next logical step is to use separate dummies for each month before and after the event. This model is specified as follows:

Individual-level fixed effects

Dummy for the period 35 months before the event (36 months before is the reference category / omitted)

$$y_{it} = \alpha + \alpha_i + \beta 1_{month\,-35} + \beta 2_{month\,-34} + \ldots + \beta 73_{month\,36} + u_{it} \quad (2)$$

Constant

Time-varying error term

Note: There are two separate estimates for people who are interviewed in the same month as the event: one estimate for those that were observed directly before the event and one for those observed directly after the event.

The only difference between Equation (1) and Equation (2) is that Equation (2) includes one dummy variable per month instead of one per year. $\beta 1$ estimates the difference in the outcome relative to the reference category (the 36$^{\text{th}}$ month before the event) for all observations that occur in the 35$^{\text{th}}$ month before the event. This implies that the estimation of $\beta 1$ builds only upon people who were interviewed in that exact period.

These *month dummies* ($\beta 1$–$\beta 73$) allow for the most flexible estimation of trajectories the data permits (the most specific date-related information available in most panel surveys is at the month level). Using these monthly observations enables researchers to compare outcomes closely around events. In turn, theoretical considerations can be formulated and tested more precisely: How strong are the effects of anticipation, how long before the event does the outcome change? Is there any sudden change from the month directly before to the month directly after the event? By zooming in more closely and exploiting month-specific information, researchers can get close to answering such questions. When working with very large data sets, these monthly dummy-estimates might be sufficiently precise to be reported and interpreted as final analyses. With typical survey panel data sets, however, monthly estimations could become noisy due to the few observations in each of the categories.

Second Extension to the State of the Art: Smoothed Monthly Estimates

Therefore, we propose a new approach, *smoothed monthly estimates*, which combines the strength of the monthly and yearly approaches. Like the monthly dummies, it leverages the full potential of the data by using its monthly information and, like the yearly dummies, it reduces noise from the estimates.

We generate a smoothed, nonparametric estimate of trajectories based on monthly estimators from the model with monthly dummies (Equations 3a and 3b). After running the regression model with the monthly dummies, we calculate predicted values (margins) for each month in the period of observation. The next step is to smooth over these monthly margins using nonparametric regression. Such nonparametric estimates have been applied in diverse disciplines, including sociology (for a review, see Andersen 2009). They are used to reduce noise in the data and identify relationships between the outcome variable and the predictor of interest without making strong prior assumptions about the shape of the association (Andersen 2009; Fan and Gijbels 1996; Gutierrez, Linhart, and Pitblado 2003).

Specifically, we run weighted local linear smoothing, which is implemented in all major statistical software (we use the *lpoly*-command in Stata) and has the broad following form (for details, see e.g., Fan and Gijbels 1996:4 ff.):

Intercept for the regression centered at month t

Error term

Sample restriction: Only months *before* the event

$$y_i = \alpha(t) + \beta(t)T_i + u, \quad for\ (T_i \in t \pm h)\ \&\ (T_i < 0) \qquad \text{(3a)}$$

Outcome = Predicted margins from regression with monthly dummies

Locally-weighted linear time trend

Local sample restriction: the month of interest (*t*) ± the bandwidth (*h*)

Sample restriction: Only months *after* the event

$$y_i = \alpha(t) + \beta(t)T_i + u, \quad for\ (T_i \in t \pm h)\ \&\ (T_i > 0) \qquad \text{(3b)}$$

To estimate a smoothed value—for example, the variable of interest at the 10th month (t) after childbirth—we first define a window around the month, covering the month itself plus and minus the bandwidth (h) of the estimation. We use a bandwidth of five months, which means that the regression model includes the values from the 5^{th} to 15^{th} months after childbirth (T). Then, a weighted linear regression is run over the monthly estimates within this bandwidth. The closer an observation is to the center of the bandwidth, the more weight it is given (following the typically used Epanechnikov distribution; see Fan and Gijbels 1996). In the regression model, the month-variable is centered at the 10^{th} month (t) after childbirth and the constant ($\alpha(t)$) is extracted and chosen as the smoothed value for this month.

This procedure is repeated for each month. For example, to estimate the value for the 11^{th} month after birth, another weighted regression is run for the observational window from the 6^{th} to 16^{th} months. The process is performed separately for the periods before (Equation 3a) and after (Equation 3b) the event to ensure that the window never includes the event. In practice, for instance, if the month of interest was 3 months before birth, the window would run from 8 months before the event until the last observation before the event (observations from the two months after birth are not included). This is done to identify a potential discontinuity at the event. These monthly smoothed estimates result in nonparametric estimation of the trajectory that can be easily displayed graphically.

The chosen bandwidth affects the results and there is a trade-off between bias and variance (Andersen 2009; Fan and Gijbels 1996). A bandwidth that is too wide will oversmooth the data, meaning that important information will get lost and the curve will be biased. A bandwidth that is too narrow leads to large variance and might overfit the data. Thereby, it might model noise rather than the true association. The choice of bandwidth depends on sample size and variance: the larger the sample and the less variance there is in the outcome variable, the smaller the bandwidth should be (Fan and Gijbels 1996). In simulations, it is possible to test how well different bandwidths work for different simulated patterns (see below). These simulation results can provide some guidance for empirical analyses. Andersen (2009) points out that the choice of bandwidth is ultimately a matter of decision by the researcher, based on visual inspection and the comparison of different bandwidths. We perform robustness checks with different choices of bandwidths.

Simulation Analysis To Compare The Estimation Strategies

Simulation: Setting Up the Data Set

To test the performance of smoothed monthly estimates compared to monthly dummies and the current state of the art of yearly dummies, we perform Monte Carlo simulations. For the simulated data set, the number of observations and between- and within-individual variation are chosen to resemble real-world data (Bryan and Jenkins 2016; Burton et al. 2006). As we will investigate life satisfaction and childbirth in Section 5, we choose three potential patterns for how life satisfaction may change around childbirth and accordingly generate simulation data to match the levels of between- and within-individual variations of women experiencing the transition to parenthood in SOEP.

To create the simulation data sets, we proceed in the following way. We create a panel data set of 2,000 individuals with six observations each (one observation in each of the three years before and after the life event). The interviews are evenly distributed over all 36 months before and 36 months after the event. The generated outcome value for each observation consists of three components. The first is the simulated underlying pattern (the dashed red lines in Figure 1). The second is a random error term that varies between individuals but is time-constant within individuals. The time-constant error accounts for the fact that people have different baseline levels of life satisfaction and may generally respond differently to the happiness scale. The third is a random error term that varies between individuals and within individuals over time. This time-varying error accounts for the fact that people's observed satisfaction can be influenced by other observed or unobserved factors, as well as measurement error. Both random error terms have means of zero, whereas the levels of variance are chosen to achieve similar levels of within- and between individuals variation in life satisfaction as in the real-world data.[1] Overall, we repeat the data generation process for each of the three simulated underlying patterns 1,000 times. The underlying pattern is the same in each iteration, but the random errors are created based on 1,000 different random seeds.

The dashed red lines in Figure 1 plot these simulated patterns for the three years before and after the event. Pattern 1 is characterized by a moderate increase in life satisfaction in the three years before birth and a moderate reduction in life satisfaction after birth. Due to the continuous and moderate up and down pattern, this pattern should be easily identified by year -group impact dummies. Pattern 2, meanwhile, indicates a sharp increase in life satisfaction starting with pregnancy around nine months prior to birth and a sharp decline during the year after birth. This pattern tests the degree to which the estimation strategies can correctly identify rapid change. Finally, Pattern 3 includes a discontinuity in the trend at the time of the birth.

Simulation: Comparing the Estimation Strategies

We use the simulated panel data set to run analyses for three proposed approaches: (i) yearly dummy estimates, (ii) monthly dummy estimates, and (iii) smoothed monthly estimates. We start our comparison of the different estimation strategies with a visual inspection of how well they identify the simulated pattern (Figure 1) and then evaluate them quantitatively (Figure 2).

Do the different estimation strategies identify the underlying pattern? Figure 1 shows the simulated patterns (dashed red line) and results from the three estimation strategies. The black dots with bold dashed lines plot the yearly dummy estimates. The blue dots represent the monthly dummy estimates and the solid blue line plots the smoothed monthly estimates.

Overall, Figure 1 shows that the yearly dummy estimates look almost identical for all three patterns. This essentially shows that the yearly dummy estimates could not clearly distinguish between the three simulated patterns. Looking at Pattern 1, the yearly dummy estimates provide a reasonable representation of the underlying pattern. However, this is not the case for the other two patterns. By design, the

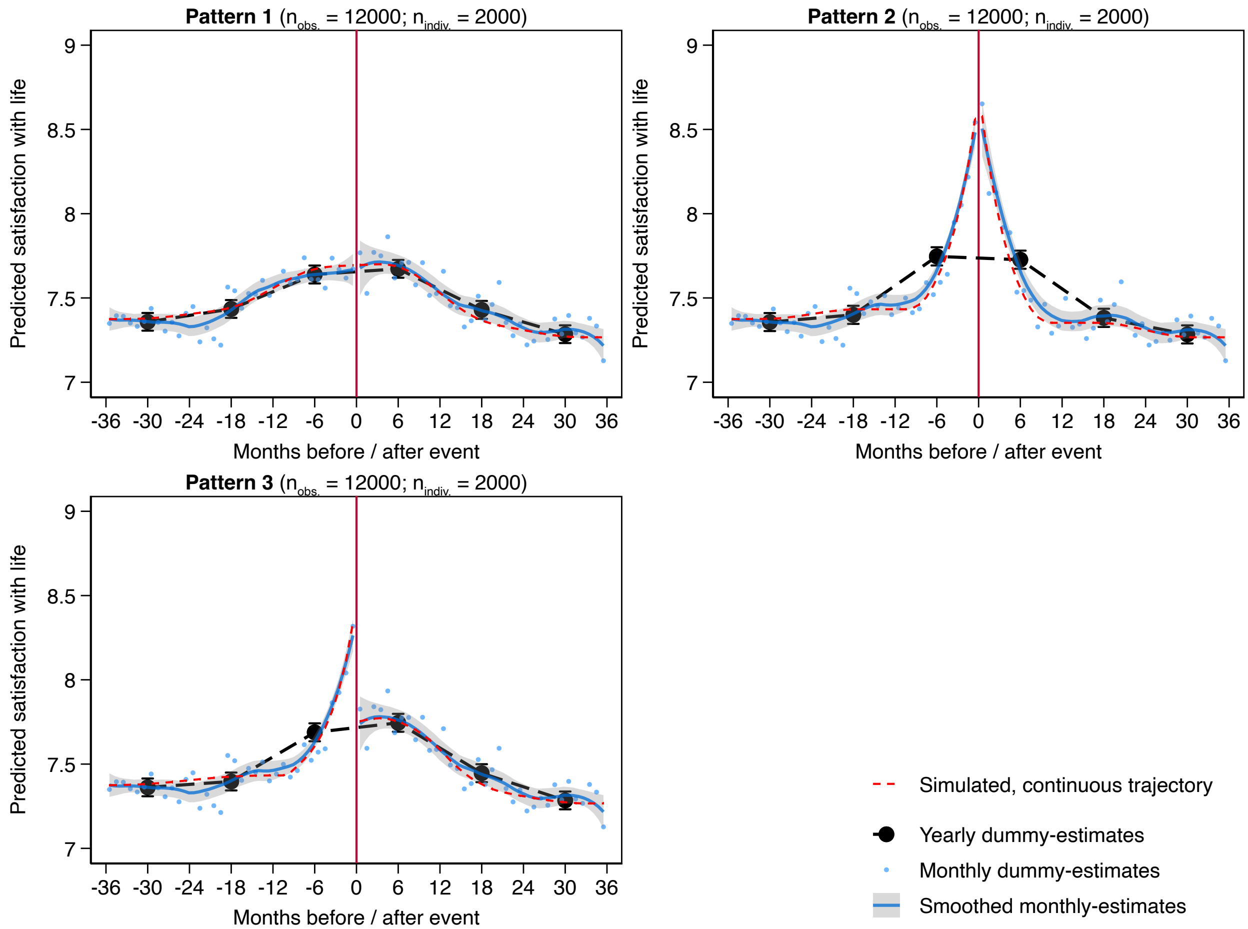

Figure 1: Simulation analyses, a visual comparison of three analytical approaches. *Note:* Comparing yearly dummy estimates, monthly dummy estimates, and smoothed monthly estimates.

yearly dummy estimates cannot identify the rapid change in Pattern 2. A researcher who interpreted the yearly dummy coefficients as indicators of the overall degree of change in people's life satisfaction would starkly underestimate how much change actually occurs. Furthermore, based on the yearly dummy estimates, a researcher would be unable to identify the discontinuity in Pattern 3. In fact, the yearly dummies estimate that satisfaction is slightly *higher* after birth, whereas the underlying pattern indicates a sudden drop at the time of the event. Therefore, the yearly dummy estimates provide unsatisfactory results for patterns that include rapid change and/or a discontinuity at the time of the event.

The monthly dummy estimates, represented by the blue dots, show high levels of variation around the simulated trend, meaning that they are relatively noisy. The blue solid lines, which plot the smoothed monthly estimates, provide good visual representations of the underlying simulated curves. These estimates capture Pattern 1 relatively well and identify the rapid change in Pattern 2 and the discontinuity in

Pattern 3. Therefore, based on the visual inspection of one simulation, the strategy of smoothing monthly dummy estimates seems to perform well.

Which of the three estimation strategies fits the underlying pattern best? The results presented in Figure 1 were based on one set of random variables. They were based on a specific random-number seed and the results would, by chance, look different for a different random-number seed. It could therefore be a matter of chance that the smoothed monthly dummy estimates performed well in the analyses shown in Figure 1.

To challenge that the conclusions drawn from Figure 1 are not just a product of chance, we compare the analytical strategies on 1,000 different generated panel data sets (each data set computes the random within- and between-individual variation based on a different random-number seed). With this comparison of 1,000 data sets, we determine the degree to which the estimates vary due to randomness (Bryan and Jenkins 2016) in order to compare and evaluate how well the different approaches describe the trajectory quantitatively. For the quantitative test, we calculate how much of the variation in the generated trajectory can be explained by the coefficients from the regressions using yearly and monthly dummy estimates and smoothed monthly estimates. We run models where the simulated values (dashed red curve) are the dependent variables and the yearly, monthly, and smoothed monthly estimates are the predictors. For the choice of the performance measure, we follow Chicco, Warrens, and Jurman (2021), who suggest using explained variance, the adjusted R^2-value, to evaluate regression analyses. In the online supplementary material, we also show results using an alternative, widely-used measure: the root mean squared error (RMSE). The analyses of adjusted R^2 and RMSE lead to the same conclusions.

Figure 2 compares the performance of the different estimation strategies for the three simulated trajectories. In each panel, the solid blue line indicates an adjusted R^2-value of 1. For Pattern 1, with its relatively minor short-term fluctuation, all approaches achieve a high level of explanatory power. However, the monthly dummy estimates are most affected by noise and perform worse than the other (monthly dummy estimates, adj. R^2=.69). The monthly smoothed estimates seem to outperform the yearly dummies (adj. R^2.94 vs. .90), but the difference is not statistically significant.

For the second pattern, with the rapid change, the yearly dummy estimates perform poorly, explaining less than half of the variation (adj. R^2=.41). The monthly dummy estimates performed substantially better (adj. R^2=.89) and the smoothed monthly approach achieves an average adjusted R^2-value of .97, indicating very high performance. For the third pattern, the yearly dummies approach performs to a moderate standard (adj. R^2=.64), whereas the monthly dummies approach performs to a relatively high standard (adj. R^2=.80) and the smoothed monthly approach performs to a very high standard (adj. R^2=.96). Overall, the results show that the smoothed monthly approach outperformed the yearly dummies for all three exemplary patterns. The improvement for estimation is rather small for trajectories with minor short-term fluctuations but high for those that involve rapid change. This implies that, when there is rapid change in the real-world, the yearly dummy estimates are not able to identify it.

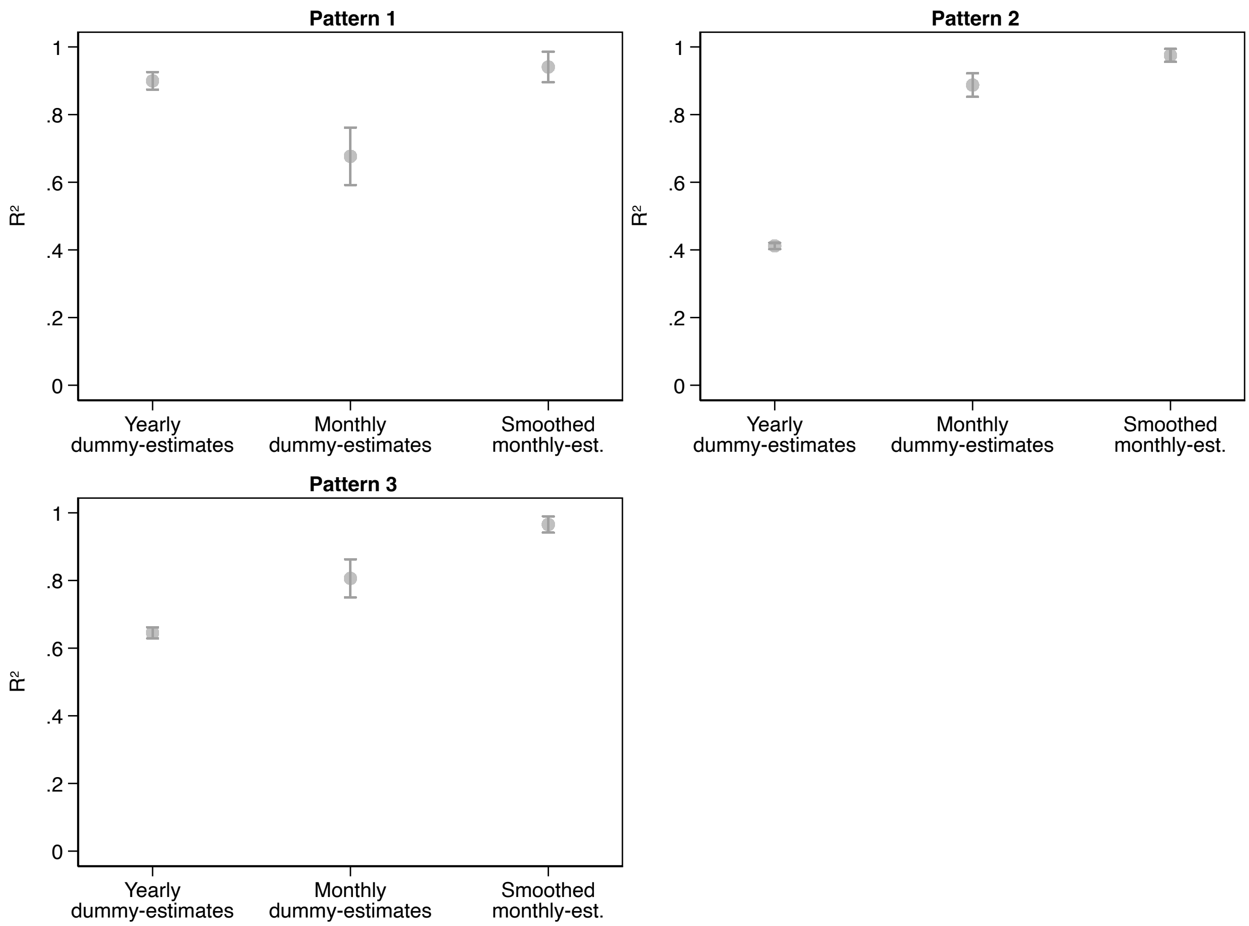

Figure 2: Simulation analyses, statistical comparison of three analytical approaches. *Note:* Comparing yearly dummy estimates, monthly dummy estimates, and smoothed monthly estimates; based on 1,000 iterations of the simulation process.

Simulation: Robustness Checks

We run further simulations to test whether the analytical approach is robust with regard to differences in sample size and bandwidth. For sample size, we test a data set that is four times as large as the aforementioned data set and one that is a quarter of its size. The smoothed monthly estimates perform roughly as well as the yearly dummy estimates for the small sample size and Pattern 1. For all other combinations of sample size and pattern, the smoothed monthly estimates outperform the yearly dummy estimates. The difference between the performance of the approaches increases with sample size (see the online supplement for details).

In the next step, we compare different bandwidths for smoothing the estimates. The main analyses used a bandwidth of 5 months. For the robustness check, we re-run all of the analyses using bandwidths of 3.33 (=5/1.5) and 7.5 (=5*1.5). A smaller bandwidth makes the curve more responsive to actual change but also to noise, whereas a larger bandwidth makes the curve less responsive, meaning that important information may get lost. Therefore, smaller bandwidths work better for larger samples, which are less noisy, and patterns with more actual change (Pattern 2). However, the overall conclusion is that the differences in terms of bandwidth are moderate within the range of bandwidths analyzed. Two researchers making different decisions concerning bandwidth (3.33 vs. 7.5) would still arrive at similar conclusions, especially when the sample is relatively large (see the online supplement for details). Overall, therefore, the approach of smoothed monthly estimates proves to be robust to variations in sample size and bandwidth.

Empirical Examples: Life Satisfaction, Childbirth, And Bereavement

To demonstrate the performance in practice, we compare monthly smoothed estimates to yearly or monthly dummies using real panel survey data. We examine changes in life satisfaction over the birth of a first child and the death of a partner. These two major life events are selected because we suspected that changes in life satisfaction in close proximity to these events might be larger than the yearly effects reported in existing studies.

Empirical Example: Data, Sample, Variables, and Analytical Strategy

We analyze data from the German Socio-economic Panel (SOEP, V37), a nationally-representative longitudinal sample based on annual interviews between 1984 and 2020 (Goebel et al. 2019; SOEP 2022; Wagner, Frick, and Schupp 2007). Due to the large sample size, low attrition rate, and rich set of variables, this data set has been used in several previous studies on life satisfaction and childbirth or bereavement (Clark et al. 2008; Dyrdal and Lucas 2013; Myrskylä and Margolis 2014; Pollmann-Schult 2014; West et al. 2019). The data preparation builds upon the files provided by the Comparative Panel File project (Turek and Leopold 2021). In addition, to identify the dates of first childbirth and death of partner as precisely as possible we use all information available in the SOEP database (see the online supplement for details).

The outcome variable of general life satisfaction was determined based on the following question: "How satisfied are you currently with your life, all things considered?". The answer scale ranges from 0 ("completely dissatisfied") to 10 ("completely satisfied"). The analytical samples cover the 36 months before and after the birth of an individual's first child and the death of a partner. It includes all individuals who were observed at least once in the 36 months before and once in the 36 months after the event.

The final sample for the transition to parenthood comprises 2,749 women ($n_{\text{observations}}$ = 14,326) and 2,545 men ($n_{\text{observations}}$ = 13,182). The sample for the death of a partner consists of 1,633 women ($n_{\text{observations}}$ = 8,840) and 663 men ($n_{\text{observations}}$ = 3,560). Table 1 shows the descriptive results for life satisfaction in the four samples, whereas Figure 3 shows how the observations are distributed around the life events.

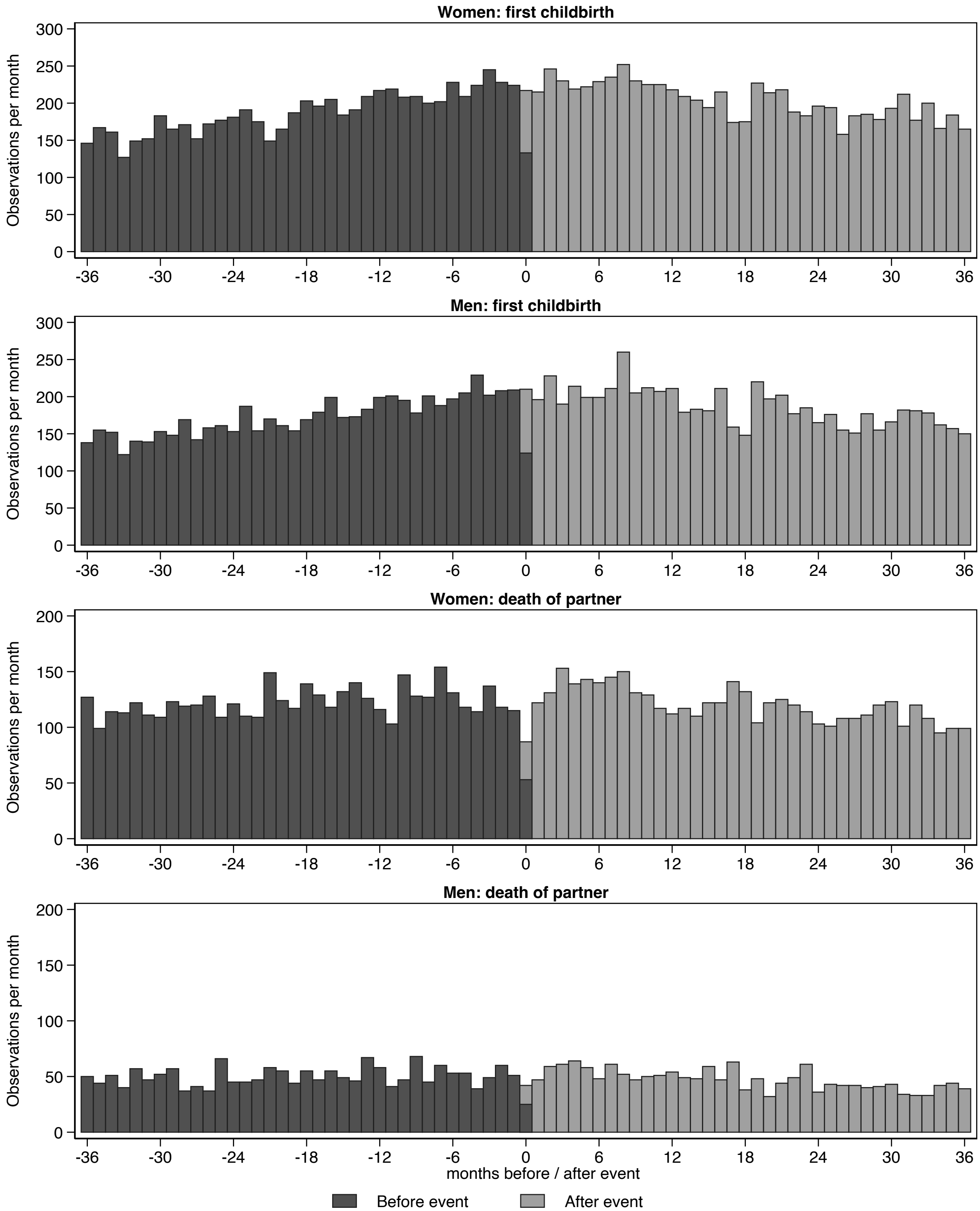

Figure 3: Distribution of sample observations relative to the life events.

Table 1: Descriptive results for life satisfaction

	$n_{individuals}$	$n_{observations}$	mean	sd_{within}	$sd_{between}$	range	histogram
Life Satisfaction							
Parenthood: Women	2,749	14,326	7.50	1.11	1.19	1-10	
Parenthood: Men	2,545	13,182	7.36	1.06	1.22	1-10	
Widowhood: Women	1,633	8,840	6.39	1.46	1.50	1-10	
Widowhood: Men	663	3,560	6.59	1.44	1.51	1-10	

The empirical analyses follow the same procedures used in the simulation analyses: we calculate and compare fixed effects regression models with (1) yearly dummies, (2) monthly dummies, and (3) smoothed monthly dummies. In line with previous research, we run separate analyses for women and men.

Empirical Example: Results

Childbirth and life satisfaction. Figure 4 demonstrates how life satisfaction changes around the time of childbirth. It uses black dots with bold dashed lines for the yearly dummy estimates, blue dots for the monthly dummy estimates, and solid blue lines for the smoothed monthly estimates.

For women, the yearly dummy estimates are similar to those found in previous research: a moderate increase approaching the birth followed by a peak in the year after birth and an ensuing decline to a level slightly below baseline (cf. Myrskylä and Margolis 2014). The monthly dummy estimates show greater month-to-month variance and almost all of them in close proximity to childbirth are above the yearly estimates. To reduce the impact of noise, the solid line smooths the monthly estimates and produces our final result. The curve shows that the increase in satisfaction starts around the time of conception (approximately nine months before birth) and increases rapidly until the child is born. After birth, there is a monotonic decline in satisfaction, which is less rapid than the pre-birth increase.

The changes in men's life satisfaction are not as pronounced as those of women, but they follow a qualitatively similar trajectory. Moreover, the difference between the yearly dummies and the smoothed monthly estimates is smaller among men than among women.

Compared to the state of the art approach of yearly dummies, the new approach of smoothed monthly estimates reveals several new findings. First, the extent of the short-term change in life satisfaction is substantially greater than previously observed. For women, the yearly dummies estimate the increase in satisfaction from baseline (the 3rd year before birth) to the observation directly before birth at 0.29 points. By contrast, the smoothed monthly approach estimates a change of 0.57 points—nearly twice as much. Second, the shapes differ. What the yearly estimates show as a sort of plateau around birth is, in fact, a remarkably sharp increase followed by a less dramatic, though still sharp decrease. Third, gender differences turn out to be greater than suggested by previous research. The yearly dummies estimated that the peak of women's satisfaction is 0.24 points higher

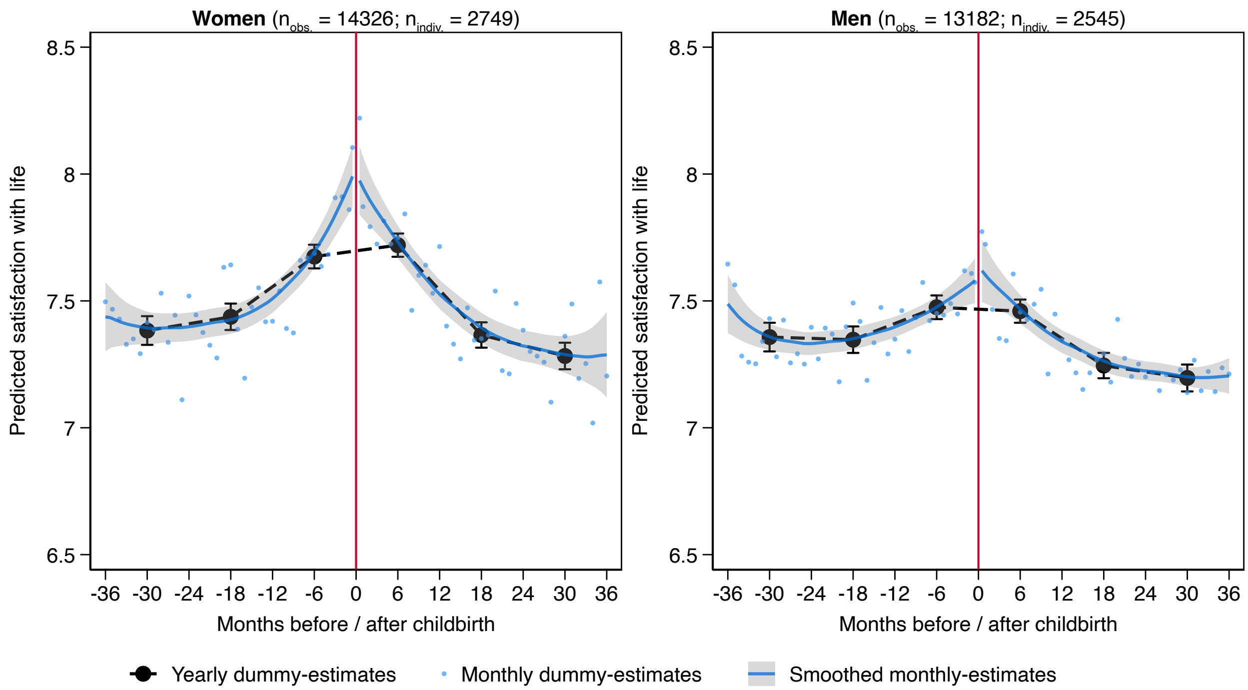

Figure 4: Life satisfaction over the transition to parenthood, based on SOEP data. Note: Comparison of yearly dummy estimates, monthly dummy estimates, and smoothed monthly estimates.

than that of men's peak, whereas the smoothed monthly trajectories estimate that women's peak is 0.44 points higher than men's peak ("peak" refers the difference between the highest point and baseline). Finally, the smoothed monthly approach makes it clear that there is no discontinuity in trends at the exact time of the birth event.

Death of partner and life satisfaction. Figure 5 shows how life satisfaction changes around the time of the death of a partner. We will first describe the results for women. The yearly dummy estimates show that life satisfaction is almost constant between the third and second year before the event and moderately lower (0.37 points) in the year directly before it. Satisfaction then declines and is 1.26 points lower in the year after birth than at baseline. There is a major recovery from the first to the second year after the event, and further moderate recovery from the second to the third year. The monthly dummy estimates have greater variation than the yearly estimates. The smoothed monthly estimates indicate a remarkable decline in life satisfaction starting approximately six months before the partner's death, as well as a strong discontinuity at the death of the partner. The estimated level of satisfaction for the month before the death is 6.10; for the month after the death, it is 5.07. Thereafter, life satisfaction increases sharply over roughly one and a half years and then levels off at a value that is moderately below the baseline.

Compared to the state of the art approach of yearly dummies, the new approach of smoothed monthly estimates identifies the discontinuity in the trend at the time of the death of the partner. As with parenthood, the smoothed monthly approach

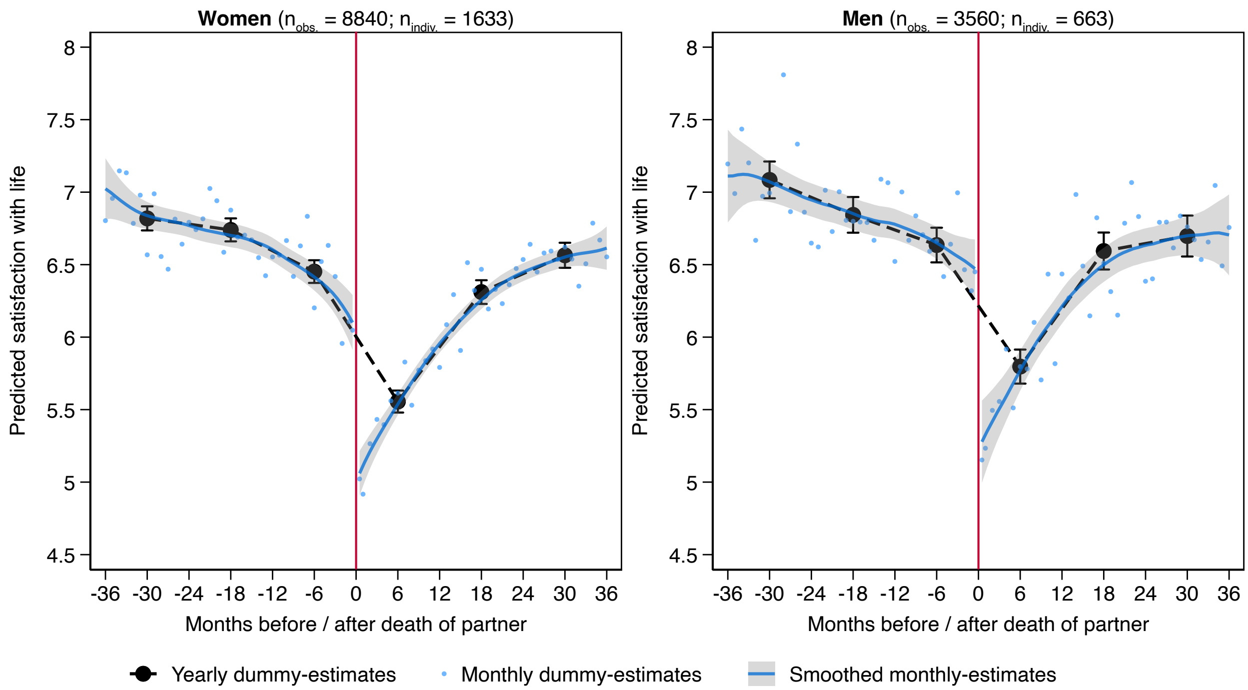

Figure 5: Life satisfaction around the time of the death of a partner, based on SOEP data. *Note:* A comparison of yearly dummy estimates, monthly dummy estimates, and smoothed monthly estimates. Overall, the patterns among men are similar to those among women. One noticeable difference is that men's pre-widowhood decline is almost linear and, unlike among women, there is no sign of a short-term anticipation.

estimates the pre- and post-widowhood delta as being substantially higher (among women, both the pre- and post-widowhood deltas are around two-thirds larger; among men, the pre-widowhood delta is estimated to be roughly equal with both approaches, but the post-widowhood delta is estimated to be almost twice as large with the smoothed monthly approach). Overall, and in a similar vein to the results for childbirth, the smoothed monthly approach shows that the life events are, in fact, more impactful than suggested by the yearly dummies approach.

Empirical Example: Robustness Checks

As with the simulation analyses, we vary the bandwidths for the smoothing to determine how they would affect the results. The results for the bandwidth sizes 3.33, 5, and 7.5 months are shown in Figures 6 and 7. The curves based on smaller bandwidths indicate slightly more change. For women and the transition to parenthood, the larger bandwidth suggests a more continuous increase in the two years pre-birth, whereas the smaller bandwidth shows an increase in satisfaction that starts more precisely around the time of conception. It seems plausible that the smaller bandwidth captures actual change in this case. However, for the death of a partner, the smaller bandwidth likely captures noise when it indicates non-monotonic trends among women in the second year before the death of their partner.

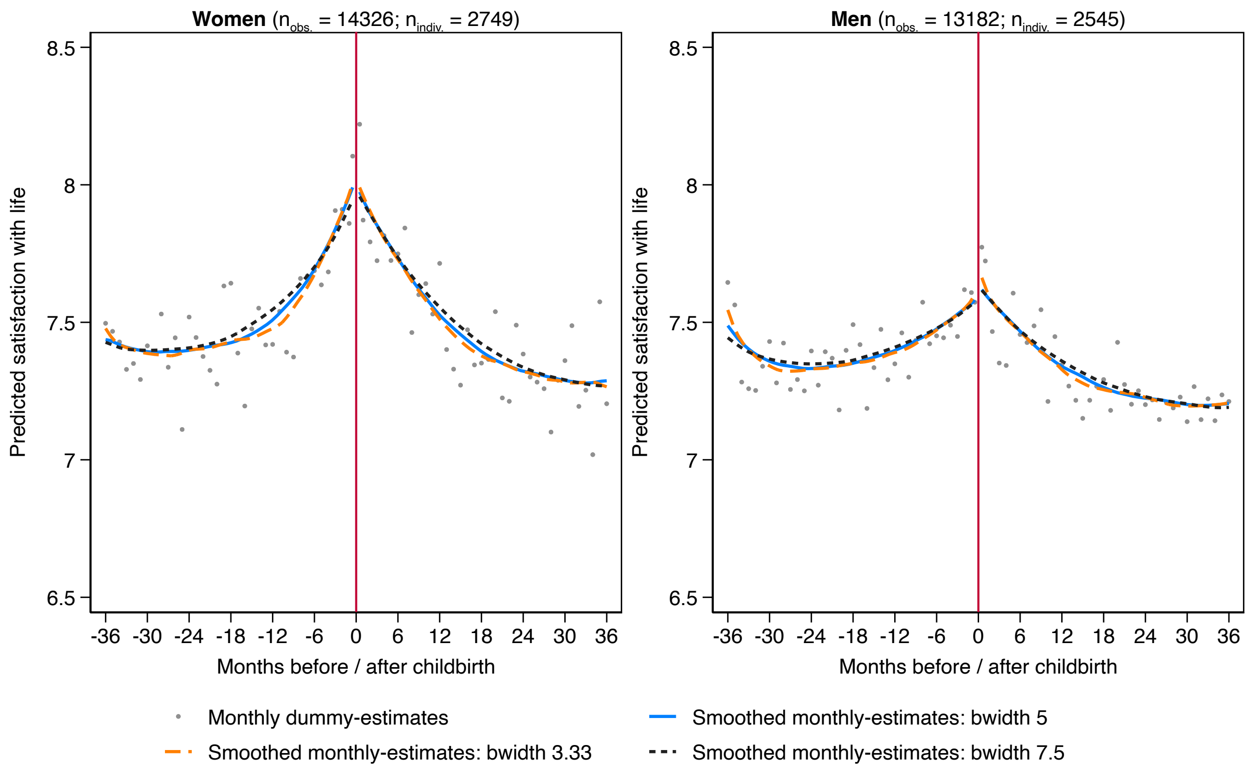

Figure 6: Robustness check for life satisfaction over the transition to parenthood. Smoothed monthly estimates with different bandwidths (different levels of smoothing).

Overall, the differences between the bandwidths are small, which suggests that the approach is generally robust to different degrees of smoothing. In any case, we suggest including different degrees of smoothing as a standard robustness check for any analyses using smoothing algorithms.[2]

A threat to the robustness of research into live events using *all* of the modelling strategies that we compared is selective survey participation. This refers to the possibility that people's willingness to respond to a survey might be affected by the event of interest. Hence, we first discuss whether and to what degree survey participation is affected by childbirth or the death of a partner. We then point out the potential consequences that selective participation might have for estimation (e.g., if the people who decline to take a survey are typically those who are hit particularly hard by a life event.)

Regarding survey participation, Figure 3 shows that there is no apparent pattern that participants engage in fewer interviews near the life event, with one exception: there are fewer interviews for women in the exact month of their partner's death. We explore potential biases further by comparing hypothetical and real interview dates. For instance, SOEP interviews annually, so if a person's 2010 interview was in June, their hypothetical next interview date would be 12 months later in June 2011. It is then possible to check whether that person actually participated in the

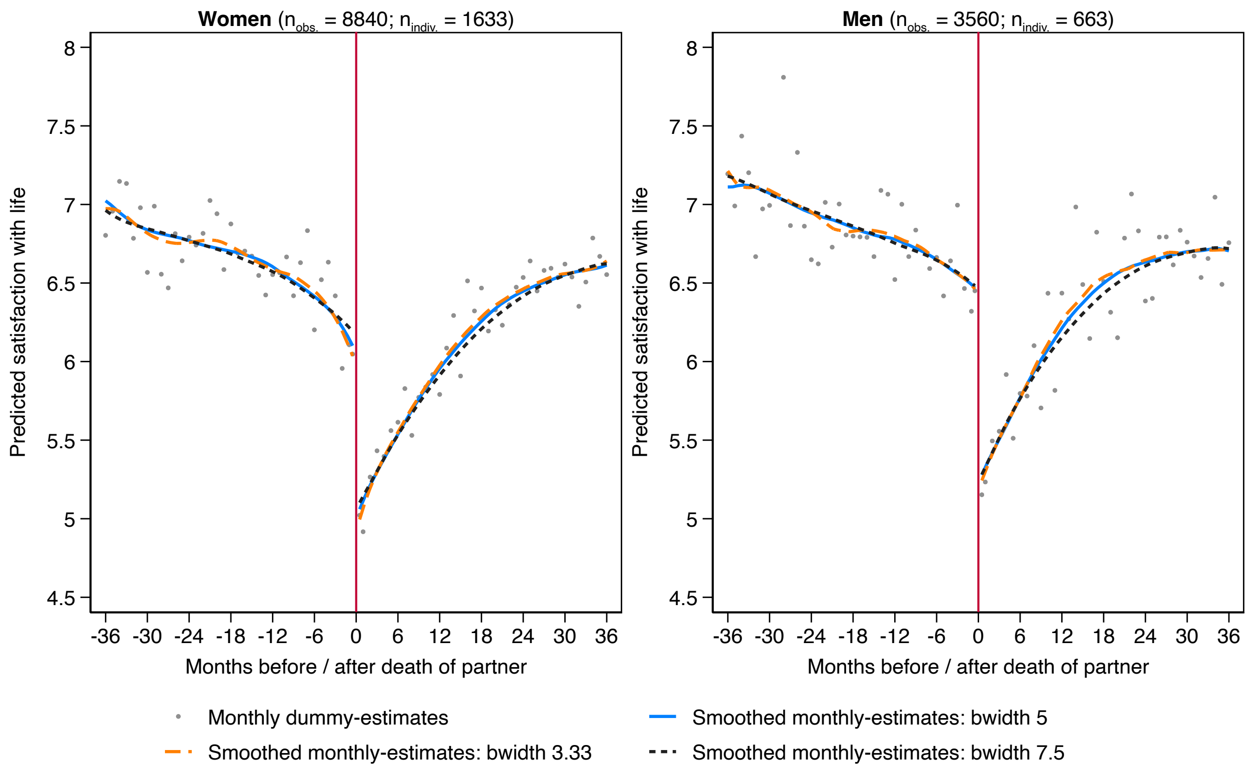

Figure 7: Robustness check for life satisfaction around the time of the death of a partner. Smoothed monthly estimates with different bandwidths (different levels of smoothing).

interview in June 2011, in a different month, or skipped the interview altogether (and their next interview was in 2012).

Compared to a baseline, mothers and fathers are approximately two percentage points more likely to skip interviews that would occur during pregnancy and roughly two percentage points less likely to skip interviews in the year after birth (Figure 2 in the online supplement). Beyond those who skip, there is no evidence for selective delays of interviews. Women who experience bereavement are around seven percentage points more likely to skip interviews in the period from around eight months before the death until around two months after the death. In addition to the skipped interviews, it seems that women tend to reschedule interviews that would have otherwise occurred in the exact month of the partner's death. For men, the pattern is less clear but similarly suggests slightly higher rates of skipped interviews around the time of their partner's death (see the online supplement for details).

The consequences of selective non-participation related to life events depend on the type of selectivity. If non-participation were only selective in the sense that people are generally less likely to participate in interviews close to a life event, this would not bias the monthly estimates.[3] However, results will be biased if participation is related to the experience of the event. In the example of the 7 percent of women who skip interviews because of their partner's death, it could be that they are those that have been hit particularly hard by the death of their partners. As a simple example to gauge the potential size of bias, suppose that the decrease in life satisfaction is approximately twice as great among those 7 percent who skip the interview as among those who participate (a decrease of 3.2 vs. 1.6 points between the baseline and the time shortly after death). In this example, the monthly dummies would be upwards-biased only by a small amount, around 0.11 points (0.07 * 1.6 points).

To summarize, for the transition to parenthood, the selective skipping of interviews is not a major issue and likely does not introduce relevant bias. Meanwhile, the highly disruptive event of bereavement does affect survey participation, but likely introduces, at worst, only a small amount of bias. Overall, selective participation is not a major issue for life events that are equally as or less disruptive than bereavement—however, this should be tested for each data set and life event analyzed.

Discussion

Recent studies have used survey panel data to analyze how diverse outcomes—such as life satisfaction, finances, attitudes, health, or housework sharing—change in response to various life events, such as divorce, having children, one's children moving out, taking care of a spouse, changing residences, volunteering, or entering the labor market (Eberl and Krug 2021; Erlinghagen et al. 2021; Kratz 2021; Mari and Cutuli 2021; Nylin et al. 2021; Schulz and Raab 2022; Torche and Rauf 2021; Tosi and Goisis 2021; Van Winkle and Leopold 2021). In short, research on changes over the course of life events is thematically diverse and thriving. Most of these studies use fixed effects regression models with one striking similarity: they analyze changes between *yearly* time intervals before and after an event. In this article, we present a novel methodological approach that leverages the month-specific data regarding the timing of interviews and life events to analyze outcomes before and after a life event in greater detail. Specifically, we propose smoothed monthly estimates. This approach runs individual level fixed effects regression, generates monthly dummy estimates around life events, and then uses nonparametric smoothing to create smoothed monthly estimates. This allows a researcher to zoom in on life events and gain new insights into more fine-grained trajectories.

First, we tested our proposed approach of smoothed monthly estimates against the current state of the art of yearly dummy estimates in Monte Carlo simulations. The findings revealed that the smoothed monthly approach outperformed the yearly dummy estimates on different types of simulated trajectories. In particular, the yearly estimates strongly underestimated the true amplitude of change in the simulated trajectories. Yearly dummy estimates can obscure relevant change. Monthly dummy estimates (without smoothing) are highly flexible and might be the first choice for studies with very large data, such as register-based data. However, they are relatively noisy for sample sizes that are typical in survey-based research. By smoothing these monthly estimates, we can achieve the best of both worlds: to detect change in the data flexibly and without prior assumptions on their functional form, as well as separate signal from noise. As the simulations illustrate, the smoothed monthly estimates perform better than the yearly dummy estimates across different simulated trajectories and for different sample sizes. The results are also relatively robust to changes in the central analytical decision: the degree of smoothing (the bandwidth used for the local linear regression). In summary, simulations show that the smoothed monthly approach is better at detecting the trajectories underlying the data under conditions typical to panel survey research.

Second, we illustrated our approach in practice and applied it to real data by analyzing changes in life satisfaction before and after childbirth and the death of a partner. The novel analytical approach revealed several new insights. In particular, it showed that the amplitude of change in life satisfaction is much larger than suggested by the yearly dummy estimates. Regarding childbirth, the positive short-term change in women is about twice as great and occurs even faster than previously known. What looked like a plateau around birth based on the yearly estimates is, in fact, a remarkably sharp increase followed by a moderately sharp decrease. The monthly dummy estimates further revealed that—for the transition to parenthood but not the death of a partner—gender differences in the trajectories are greater than previously assumed. Finally, the smoothed monthly estimates can detect discontinuities in trends at the moment of the life event. They revealed that this is the case for bereavement but not the transition to parenthood. The finding that life satisfaction trends are discontinuous at the death of a partner is certainly no surprise. There are, however, other applications where it is not obvious whether such discontinuities exist or not, and our proposed approach can detect this. For instance, are there life events that lead to a sudden change in attitudes and an observable discontinuity in, for example, trends in political or gender role attitudes?

The central aim and contribution of this article is methodological, although the empirical results do also allow for some broader, more substantial conclusions. The empirical analyses here are more in line with baseline theory than previous studies that relied on yearly dummy estimates (Headey and Wearing 1989); that is, they show that satisfaction changes rapidly in response to a life event and then quickly returns to values that are close to the pre-event level. In fact, the findings suggest that there might generally be more change in people's life satisfaction across the life course than previously known. Future applied research can determine whether this pattern of greater change than previously assumed is also true for other life events and other sociologically-relevant outcomes, such as interpersonal contact, gendered division of housework, or various attitudes.

It is also important to consider other research questions to which this method can be applied. In general, this method can be applied to any outcome variable, such as attitudes or feelings, behaviors, income and other labor market traits, and health characteristics; in combination with any life event, including transitions in work or family life or residential moves. Let us go back to the Law of the Instrument: a boy or girl trained in using a hammer will search for and pound the remotest nail but ignore the loose screw in plain sight, or, applied to research practice: "[. . .] a scientist formulates problems in a way which requires for their solution just those techniques in which he himself is especially skilled" (Kaplan [1964] 1998:28). If a researcher's toolbox is filled with tools that are less susceptible to short-term changes and potential discontinuities, this might motivate them to formulate research questions in such a way that short-term changes are not central. However, when a researcher has a new tool at hand, which they can use to identify short-term changes as well, they might also tackle research problems and questions that center around them.

The central strength of the proposed methodological approach is that it enables researchers to reveal novel insights and answer additional research questions without having to collect new data. Indeed, many data sets, such as SOEP, Understanding Society, or the National Longitudinal Survey of Youth already contain all the necessary information (for an overview of available and harmonized household panel studies, see e.g. Turek and Leopold 2021). This illustrates the immense and still partially unexploited potential of large multi-thematic surveys. Hence, this article makes the following central claim: "There's more in the data."

Notes

1 The time-constant error term has a standard deviation of 1.1 and the time-varying error term has a standard deviation of 1.2. For a comparison with real-world data, see Table 1.

2 For Stata-users, this is simply done in the "bwidth" option of the *lpoly*-command.

3 It would, however, bias the yearly estimates because they would be averaged over a group where the months close to the death (with particularly low satisfaction levels) are underrepresented relative to the months further away from the death (when life satisfaction is relatively higher).

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