Longitudinal Research

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Some have argued that "[a]ttention to change over time is the hallmark of studies of human and family development" (Menaghan & Godwin, 1993, p. 260). Scientific studies often stress the recency and relevance of data because historical time looms large for understanding why and how families change, develop, and interact. In this chapter, we introduce why studying time matters, discuss major developments in longitudinal methods, and provide examples of how to match research questions with longitudinal analytic models.

The Significance of Temporal Ordering

Temporal ordering is crucial because "development," whether human, relational, social, or otherwise, concerns change over time. Even if a research question simply seeks to explore links between two variables or describe a single phenomenon, things may change tomorrow and again after that. Will our observations persist? For how long? Can they be measured the same way after a month, year, decade, or even a century from now? Researchers since the 1930s (such as Burks et al., 1930; see below) have focused on longitudinal family and child outcomes. But motivations to study time are not rooted in the truism that things change; the consequences of change are what matter to social scientists. If A and B are strongly linked today,

Supplementary Information The online version of this chapter (https://doi.org/10.1007/978-3-030-92002-9_24) contains supplementary material, which is available to authorized users.

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K. Adamsons et al. (eds.), *Sourcebook of Family Theories and Methodologies*,
https://doi.org/10.1007/978-3-030-92002-9_24

what happens if A changes? What about causality (which cannot be established without considering time)?

We argue that two goals, establishing causality and assessing change/development, are the primary reasons why time matters to family researchers. Mill (1882), drawing on Hume (1739), articulates three conditions to establish causality and strengthen developmental claims: temporal ordering (x must precede y), covariance (when x changes, y does too), and elimination of alternative explanations. Cross-sectional data may, under rare circumstances, satisfy the latter two conditions, but never the first. If x and y were collected simultaneously, we cannot know which came first. Longitudinal research often provides our best view of ordering temporal processes.

Major Developments in Longitudinal Family Research Methods and Longitudinal Datasets

Family scientists' interest in within-individual change has led to a heavy focus over the past half century on panel surveys (Menaghan & Godwin, 1993). Over the past 30 years, panel studies have exploded. Today, many large, often publicly available, datasets contain family information (Some of these are listed in Supplemental Table 1).

Analyzing Longitudinal Data

The increase in longitudinal data availability was accompanied by an increase in longitudinal data analytics. We provide a brief history of the analysis of longitudinal data and trace developments in the field, driven primarily by the advent of modern computing power.

Measurement

The quality of longitudinal claims is linked to improvements in measurement quality. If used appropriately, advances in measurement can boost confidence in claims made from longitudinal data, especially because longitudinal data is susceptible to temporal variation in measurement error (Menaghan & Godwin, 1993). Because family researchers often use data from multiple family members (e.g., Karney & Bradbury, 2005; Qian, 2018), the impact of measurement error on parameter estimates is likely to be cumulative rather than subtractive (Bound et al., 2001). Subsequently, researchers employed exploratory factor analyses that more accurately model the underlying construct and its error structure(s) (Menaghan &

Godwin, 1993), leading to a boon of factor analytic approaches to measuring family-related phenomena in the mid-1990s (Asher, 1997; de Vries, 2006; Roosa & Beals, 1990; Sabatelli & Waldron, 1995; Stephens & Sommer, 1996).

Since the late 1990s, the research community has borne witness to an influx of complex models to assess and account for measurement error. These include item response theory (Gordon, 2015), confirmatory factor analysis (Schumacker & Beyerlein, 2000), and various latent measures made possible via structural equation modeling, including for models where the causal effects can flow in multiple directions (Price et al., 2019). These models allow researchers to examine if and how measurement error influences their model.

Analysis

Family scholars have embraced advanced statistical techniques for analyzing longitudinal data. In their landmark book, Singer and Willett (2003) developed a framework for examining, describing, and modeling change. Other books on analyzing longitudinal family data followed, including Kline's (2005) book on structural equation modeling. Nagin (2005) emphasized group-based (sometimes called "person-centered" vs. "variable-centered") analyses that demonstrate how change can be conceptualized and analyzed as a series of trajectories, whether latent class, latent growth, or latent profile analyses, for individuals or dyads. Dyadic data can be analyzed with the common fate growth model or the actor-partner interdependence models (Cook & Kenny, 2005; Ledermann & Kenny, 2012). Finally, the work of Bengt and Linda Muthèn has been critical, both because of their influential papers throughout the statistical and psychological literature but also due to their statistical program, Mplus (statmodel.com).

Table 1 displays a sample of the type of statistical models researchers can use to study families across time. While we do not discuss each of these in detail, a large group of tutorials are readily available for researchers to consult on these topics and many others (Barbeau et al., 2019; Byrne, 2012; DeMaris, 1995; Heaton, 1995; Johnson, 1995, 2005; Jung & Wickrama, 2008; Kuiper & Ryan, 2018; Luke, 2004).

Connecting Longitudinal Questions with the Appropriate Method

In this chapter, we cover four statistical techniques commonly employed by family researchers – multilevel models, structural equation models, group-based trajectory models, and survival analysis. We give a brief overview of each method and discuss the types of questions researchers might answer with each one. Throughout, we use the example of how premarital cohabitation is linked to subsequent marital

Table 1 Sample of longitudinal models that can be applied to family relationships

Type of analysis	Time points required	Most common distribution of outcome variable
Change score analysis[a]	2	Continuous
Repeated measures ANOVA	2	Continuous
Cross-lagged model[b]	2	Continuous
Growth curve[c]	3	Continuous
Mixture models (growth, regressions, finite)[d]	2 (but more strongly preferred)	Categorical/continuous
Survival analysis (e.g., event history, discrete-time, cox)[e]	3	Dichotomous
Fixed vs. random effects[f]	2	Categorical/continuous

Note. [a]Johnson (2005), [b]Kuiper & Ryan (2018), [c]Luke, (2004), [d]Jung & Wickrama (2008), [e]DeMaris (1995), Heaton (1995), [f]Johnson (1995)

outcomes using CREATE data. The CREATE study is a nationally representative, longitudinal study of 2181 young married couples (James et al., in press). Our goal is to give readers a conceptual idea of why one might employ a particular method, without discussing the nearly endless available extensions.

Multilevel/Hierarchical Regression Models

Overview

Multilevel models, or hierarchical regression models,[1] are one of the most common ways of modeling longitudinal data. Data are collected at different conceptual "levels" (individual, family, school, community, etc.), requiring the use of statistical models that account for variance at each level. Theorizing at multiple levels is crucial to family research because individual family members (one level) belong to families (another level). Because people are "nested" within various contexts (e.g., families, schools), assuming that relationships at one level operate similarly at another level can lead to imprecise estimates and erroneous claims.

Because people, families, and organizations change over time, we also need to view time as a level. Although people's motivations, values, behaviors, and actions are likely to be linked to and influenced by their prior motivations and behaviors, time itself gives context and shapes these same phenomena. Rather than assuming that everything occurs at the same level, it is preferable to examine how group-level influences (including time) can shape or be linked with an outcome. For instance, the influence of premarital cohabitation may fade over time within an individual

[1] These should not be confused with what some have called hierarchical regression, which is not a type of regression but merely sequentially entering variables into a model.

relationship. Similarly, differences in marital quality that favor non-cohabitors may fade over time as stigma associated with premarital cohabitation fades.

There are, of course, statistical reasons for multilevel models as well. Observations belonging to the same group or person tend to be correlated with each other, violating the independence assumption of linear regression. Thus, using individual-level statistical tools like linear regression to examine group or longitudinal processes is problematic (Snijders & Bosker, 2012).

Linking Questions

Questions about change over time are particularly suitable to multilevel models, as they allow researchers to assess average levels of a given phenomenon over time. Multilevel models also easily accommodate questions about within- (inter) and between- (intra) person change. For instance, researchers may want to model marital quality over time to examine whether changes in marital quality are different for cohabitors and non-cohabitors, consistent with prior research (James & Beattie, 2012). Alternatively, researchers could also examine individual characteristics that predict changes in marital quality over time, such as personality traits.

Additionally, multilevel models allow researchers to examine cross-level interactions, where a variable at one level interacts with a variable at another level. For example, one could ask whether personality characteristics (within individuals) affect marital quality in the same way for cohabitors and non-cohabitors (between individuals).

Example: Differences in Marital Commitment between Cohabitors and Non-Cohabitors over Time

Commitment, key to understanding relationships, changes over time. Marital commitment may be strongest at the outset then wane as challenges arise. Less committed couples may separate, leaving only committed marriages, advancing the erroneous conclusion that commitment increases over time.

We used multilevel models to examine change across four waves of marital commitment between cohabitors and non-cohabitors in our CREATE data. Because the data are dyadic, we fit separate models for partner 1 (female except in male-male marriages (n ~ 25)) and partner 2 (male except in female-female marriages (n ~ 50)). We examined how cohabitation was related to initial levels (intercepts) and change (slopes) across time in commitment.

We used Stata's XT suite of commands to estimate the models. We initially estimated the overall pattern for marital commitment across the first four waves of CREATE data, controlling for age, education, sex, income, whether the couple had children living with them, and race/ethnicity. For both members of the couple, we observed similar patterns of change in marital commitment over time, with initially high levels of commitment at the first wave, followed by a somewhat steep decline at waves 2 and 3 and a subsequent rebound by wave 4. Overall, the pattern resembles a fishhook.

Substantively, we were interested in whether cohabitors have a different pattern than non-cohabitors. To test this possibility, we included a variable for whether the couple cohabited prior to marriage as well as an interaction term with wave. The results are found in Supplemental Table 2 and are graphically displayed in Fig. 1. We found evidence of differences in initial marital commitment between cohabitors and non-cohabitors for both couple members, with cohabitors reporting lower levels of marital commitment at the first wave. The interaction with wave suggested that for partner 1, this initial difference in marital commitment remained constant over time. In contrast, for partner 2 the difference in marital commitment between cohabitors and non-cohabitors shrunk over time. In sum, using multilevel modeling allowed us to explore associations between cohabitation and marital commitment in a longitudinal dataset, while accounting for nonindependence due to repeated measures.

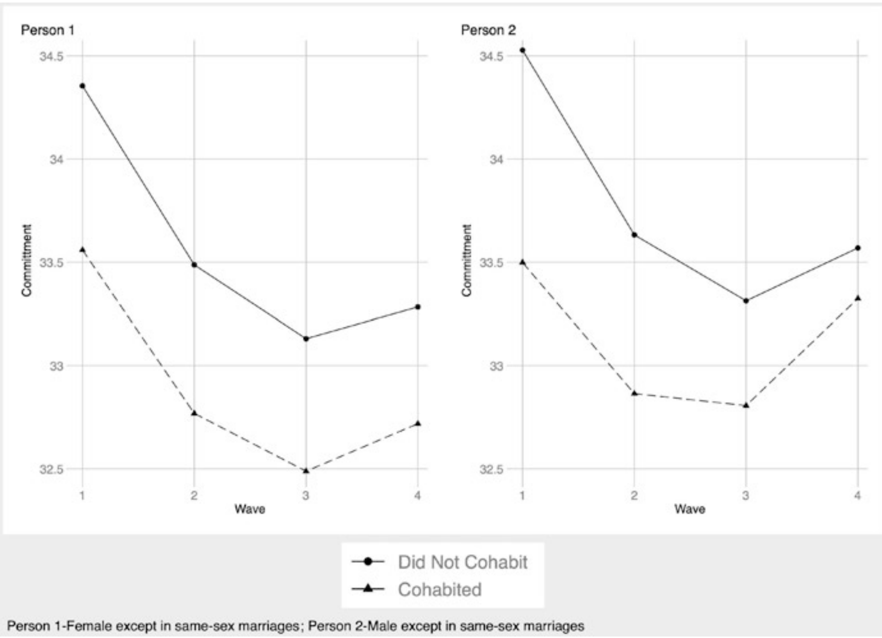

Fig. 1 How marital commitment changes over time between cohabitors and non-cohabitors

Structural Equation Models

Overview

Structural equation models (SEM) emerged from a desire to model data in ways that better match reality. For instance, we may believe that health matters in marriage (Yorgason & Choi, 2016) and wish to see if cohabitors are more likely than non-cohabitors to experience health problems over time and thus poorer marital quality, consistent with a selection into marriage hypothesis (James & Beattie, 2012). In this example, health is both a dependent variable (cohabitation is linked to health) and an independent variable (health is linked to marital quality). Linear regression allows a variable to be an independent or dependent variable but not both. SEM models allow researchers to model health as both a dependent and independent variable simultaneously. By solving multiple regressions simultaneously, we obtain more efficient and less biased estimates and standard errors.

Linking Questions

SEM

SEM is uniquely suited for several purposes, such as examining mediation and assessing measurement (Little, 2013). Here we focus on another strength of SEM—examining dyadic data, or data that are measured simultaneously by two people within the same family. Family members' lives are interrelated, and our statistics need to reflect this non-independent reality. SEM provides a simple way of doing this by correlating variables or residuals across family members, or by modeling predictors from one family member in relation to outcomes of the other family member. In this way, we can address important relationship focused questions (e.g., actor-partner interdependence or common fate models)

Example: Changes in Commitment Patterns between Cohabitors and Non-cohabitors

For this example (see Fig. 2), we chose to examine (partner-only) bidirectional change in reports of commitment as predicted by cohabitation, using a dyadic random intercept cross-lagged panel model (RI-CLPM; Hamaker et al., 2015). Because spouses' commitment levels are likely interrelated, the analytical model must be capable of assessing bidirectional effects. SEM is ideal, as it is the only model among our four examples capable of this. Recent work on these models has separated between- and within-person variability by estimating a random intercept. The

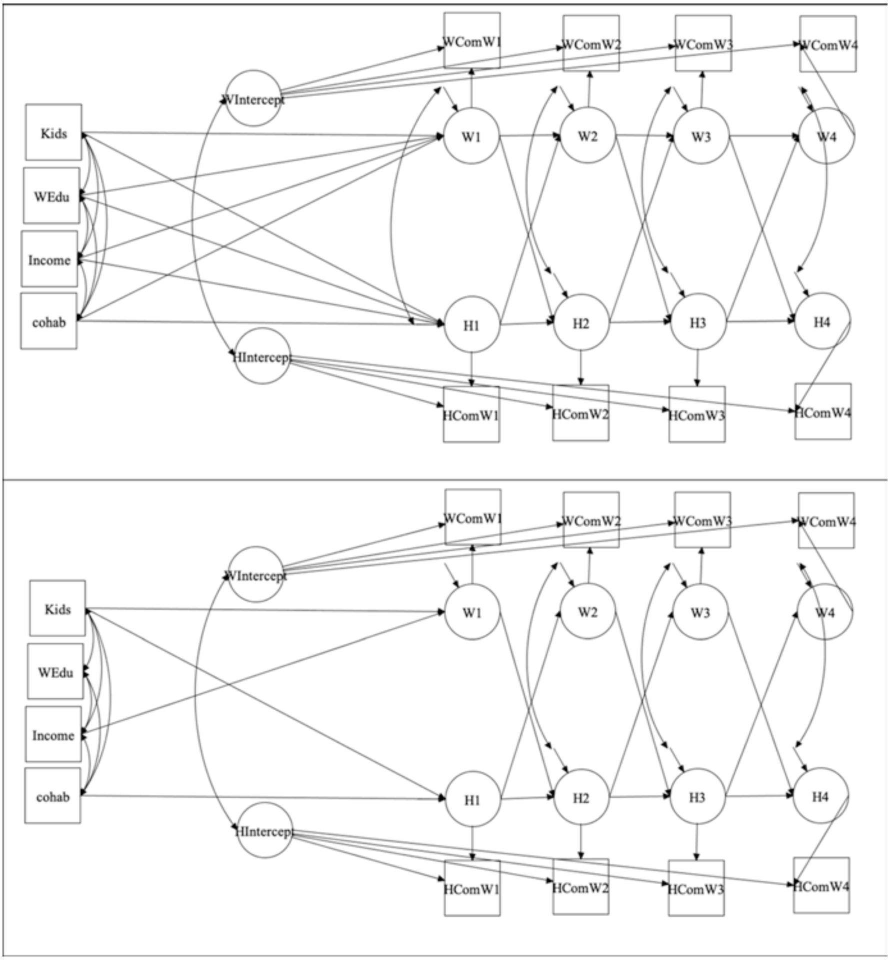

Fig. 2 Random intercept cross-lagged panel model examining within-person connections between husband and wife commitment levels across time, as predicted by cohabitation (full model in top panel, significant paths shown in bottom panel). (Note: *W* wife, *H* husband, *Edu* education, *cohab* cohabitation prior to marriage, *Com* commitment to the marriage)

RI-CLPM approach estimates a unique, random intercept for each construct of interest, which captures between-person or inter-individual characteristics across time (or a person's average across time). The cross-lagged paths then represent within-person or intra-individual change across time. In this example, we examined the interrelationship of longitudinal commitment between partners using cross-lags of commitment levels and then examined whether premarital cohabitation predicted intra-individual change in commitment levels of both spouses.

As seen in Fig. 2, results from the RI-CLPM suggest that within-person changes in commitment in partner 1 (mostly wives) were significantly positively associated with changes in partner 2 (mostly husbands) commitment a year later. Similarly, within-person changes in commitment in partner 2 were also associated with changes in partner 1 commitment a year later. These findings confirm bidirectional associations in within-person changes in commitment for partners in young married couples. Random intercepts for partners were significantly correlated (r = 0.45), suggesting a moderate level of overlap in between-person variability or overall averages across time of commitment for both partners. Cohabitation prior to marriage was negatively associated with within-person changes in commitment for partner 2 but not partner 1. This finding suggests that when couples cohabited prior to marriage, they also report experiencing less fluctuation in commitment.

Mixture Models

Overview Many statistical models, including most longitudinal multilevel models like latent growth curves, assume that a single trajectory over time can meaningfully capture the experience of most individuals in a given population, despite theories and evidence suggesting this is unlikely to accurately represent reality. Group mixture models, a particular application of finite mixture models, allow researchers to test the assumption of a single group trajectory and instead show subpopulations with distinct trajectories (Jung & Wickrama, 2008). Consequently, mixture models allow researchers to show qualitatively different patterns of change across the distribution. In some instances, mixtures may represent actual groups present in the population. More commonly, however, they represent a statistical estimate of a more complex distribution of trajectories, summarized as parsimoniously as possible (Wickrama et al., 2016).

Linking Questions

Group mixture models allow researchers to get around the question that often underlies the relationship between theory and empirical findings, namely, which theory is most accurate (or even "true"). Instead, these models allow us to answer questions such as "under what circumstances is this theory most accurate? For whom does it make the best predictions?" Similarly, if researchers believe that the effect of one variable on another might not be homogeneous (i.e., heterogeneous effects), group mixture models can often be helpful. Importantly, this can apply to heterogeneous change patterns (growth trajectory models) or on differing effects of variables on outcomes (regression-based mixture models).

For example, the influence of cohabitation on relationship quality may vary. Cohabitation may, for some, be a considered choice and improve marital quality (i.e., successful trial marriage). Others, reluctant to forgo relationship-specific capital (e.g., children, pets, joint networks), may choose suboptimal marriage partners, decreasing subsequent relationship quality. Or cohabitation may not matter because cohabitation has largely become a normative part of relationship development. To test this idea, one could employ group-based trajectory models with longitudinal data that examined measures of cohabitors' relationship quality over time.

Example: Differential Effects of Cohabitation on Marital Satisfaction

We examine whether there are discernible differences in marital satisfaction[2] trajectories among partner 1 (mostly wives in opposite sex marriages) that cohabited prior to marriage using a latent class growth analysis approach, estimated using Mplus. The top panel of Supplemental Table 3 online shows various model fit indices, used to select the number of retained classes. Substantive interpretability, strongly rooted in theory and conceptualization, should be a primary concern when deciding on the number of classes. We have followed that approach here, aided by the statistical measures Mplus provides.

We decided on a two-class approach for several reasons. The two-class solution is substantively interpretable and in line with our prior theoretical predictions. The two-class solution shows statistical improvement over a model with one class (see the LMR p-values as well as decreases in LL, AIC, BIC, and a BIC relative to the model with 1 less class), yet a three-class model does not. The two-class solution also shows reasonably high, though less than perfect, entropy and has no classes less than 5% of the sample (which can be a sign of a residual class). Finally, the model had no estimation issues, which can be an indicator of suboptimal model fit.

The substantive results are found in the bottom panel of Supplemental Table 3 online and include the intercept as well as the linear and quadratic slopes for each class (C1 and C2, respectively). C1 was the largest class comprising 77% of the sample, and C2 included the remaining 23%. Each class showed a distinct pattern of change in partner 1 relationship satisfaction over time; for ease of interpretation, the predicted change patterns of each group are shown in Fig. 3. Partners 1 in C1, the largest of the two groups, began with relatively high levels of satisfaction that declined at a modest pace that slowed over time, flattening out by the fifth year of marriage. In contrast, the second and smaller class began at much lower levels of satisfaction and experienced a much steeper decline in marital satisfaction compared to C1.

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[2] We measured marital satisfaction based on a scale consisting of questions asking how satisfying, rewarding, warm and comfortable, and happy the marriage is. Cronbach's alpha values varied between 0.94 and 0.95 across the four waves. The scale varied between 0 and 21, with higher scores indicating higher overall satisfaction. Note that we present weighted results.

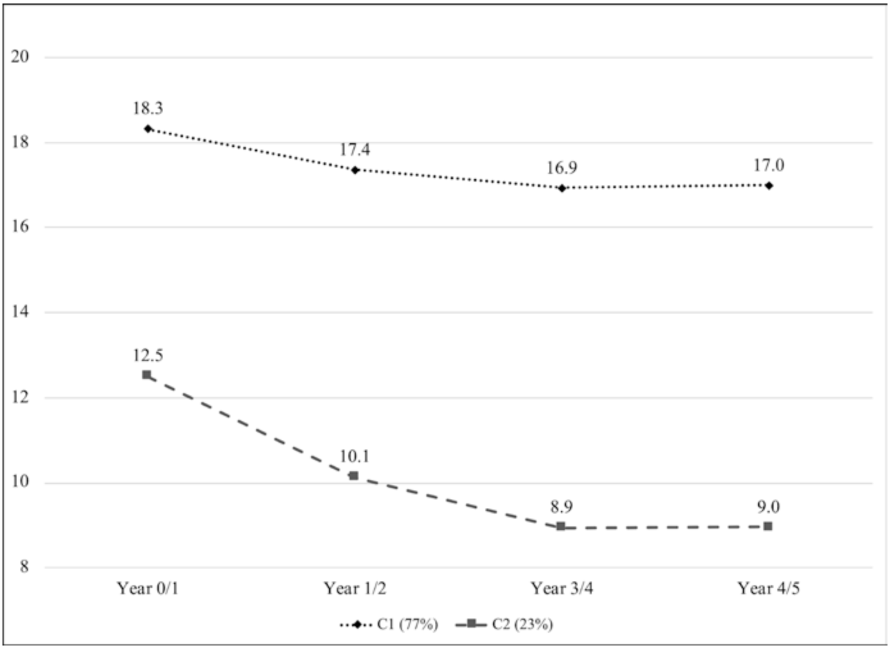

Fig. 3 Marital satisfaction among premarital cohabitors over the first 5 years of marriage, CREATE waves 1–4

Researchers can also include time-varying or time-invariant predictors of class membership[3] in this type of model. We included (see Supplemental Table 3 online) age, education, sex, income, whether the couple had children living with them, and race/ethnicity as predictors of class membership. We found that couples with higher incomes were more likely to be in class 1 and those with children in class 2. Blacks were more likely than whites to be in class 2.

Survival Analysis

Overview

Survival analysis is among the least commonly employed longitudinal methods in the family sciences. It merits greater attention because it focuses on *when* events occur, making change an inherent part of the model. To estimate survival models, statisticians reshape the data so each observation period has one observation (often

[3] It is also possible to include distal outcomes or predictors of the individual classes' intercept and slopes.

called “person-years” or “person-months” when each person is observed across a series of years or months). By placing each person-year (or person-month or any other time-based phenomena) on its own row, handling time-varying covariates becomes easier because researchers can match person-years with the corresponding value from the time-varying (or time-invariant) variable. Dropping all time points after the event occurred for an individual person (if the person first cohabited at age 25, all time points at age 26 and beyond would be dropped for that individual) eliminates worries about temporality and reverse causation. Many issues of censoring are no longer relevant, since the question becomes whether one has observed the event in question in that specific time period, which can now be accurately assessed (yes/no).

Using techniques and estimation procedures such as the Kaplan-Meier or life table methods for survivor functions, or proportional hazards (among others; see Lee & Wang, 2003), one can then employ a range of regression models such as binary logistic, probit, or accelerated failure time to develop a statistical model that examines when, why, and how people enter their first cohabiting relationship. Readers seeking to know more are directed to the wide assortment of literature on survival analysis methods, including Cleves et al. (2010) and Allison (2004).

Linking Questions

Imagine one wanted to know more about when people first move in together (whether premaritally or upon marriage). The age at which this occurred would be crucial, but other explanatory factors exist that help us better understand when, why, and how people cohabit for the first time. To explore this, one would collect event history data that recorded when events occurred to a (preferably large and representative) group of individuals (e.g., Bellani & Esping, 2020). Because not everyone chooses to cohabit prior to marriage, these individuals would not have a value for the cohabitation variable (censoring). Then one would collect data on explanatory factors, such as parental marital status, relationship history, education, sexual orientation, etc. Some of these variables would be time-invariant, such as parental divorce status, whereas others, such as income, might change over time (time-varying covariates).

Example: Similarity in Attrition Rates between Cohabitors and Non-cohabitors

In this example, we explored whether cohabitors were more likely than non-cohabitors to drop out of the CREATE sample. We began by creating variables indicating whether either or both members of the couple participated in each wave.

We used these variables to create a "time to failure" variable that measured when a given couple attrited from our sample. We censored observations that remained in the sample throughout the first four waves.

Because survival models focus on event occurrence over time, many programs provide ready-made graphs that display initial and adjusted trends over time. Two of the most common of these are Kaplan-Meier survival and Nelson-Aalen cumulative hazard estimates. Figure 4 shows these for our data, broken down by cohabiting status (note that these graphs are merely the inverse of each other but scaled differently). Overall, the trends suggest that any difference in attrition between cohabitors and non-cohabitors is likely to be minimal. To formally test this, we employ a Cox proportional hazard model, found in Supplemental Table 4 online. Here, we predict time to drop out for *both* members of the couple. The independent variables except cohabitation (a couple-level variable) come from partner 1 (female except in male-male marriages). Confirming prior results, we found no evidence of differences based on cohabitation status, but we did find age and education differences, with younger respondents less likely to drop out, along with couples with more education. We found no differences for sex, income, whether the couple had children living with them, and race/ethnicity.

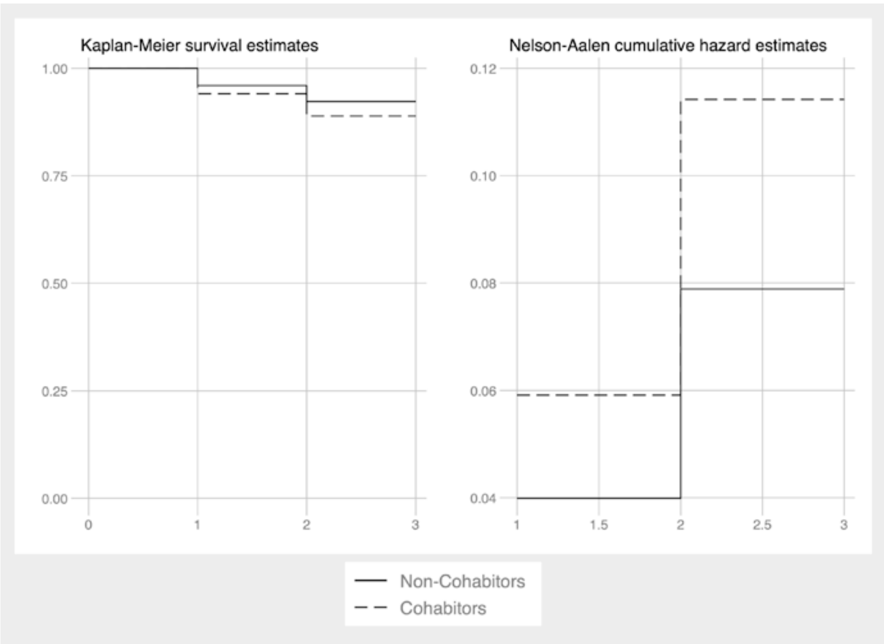

Fig. 4 Survival and hazard estimates of study attrition

Conclusion

Methods and models flexibly integrate multiple insights about how change over time informs questions about families, now and in the future. The rapid development of longitudinal methods, paired with increases in computing power, allows researchers to do just that. Further, the rise of nationally representative, longitudinal datasets enables researchers to more accurately assess contemporary family patterns.

However, enthusiasm for longitudinal research in the field of family science should be tempered by some important limitations. First, researchers must always ensure their claims match their methods – highest quality claims must always be paired with the highest quality methods. If a sample is not representative, for instance, researchers should refrain from implying that their results apply more broadly than warranted by their sample.

Similarly, findings using less than optimal methods are, in many instances, published first, making it difficult for more accurate (and complex) assessments to find space in the academic literature. While statistical complexity is not superior *ipso facto, statistical models that better account for complexity should be given greater weight than other models in the publication process, particularly since replication should be a scientific stanchion.*

Future Directions

Issues about data collection, measurement and conceptualization, and increasingly sophisticated analyses will hold an even more central place in the future than they do today. If we wish to establish solid scientific claims, longitudinal data are necessary but not sufficient. Longitudinal data often demonstrate that previously unconsidered alternative explanations may be key to understanding the phenomena studied, especially as the magnitude or even direction of effects shift over time. Although families are constantly changing throughout the world, changes seem to be occurring at an increasing pace in recent years. Political and social trends in many high-income countries suggest that society is becoming increasingly split along geographic, religious, socioeconomic, and political lines. As divisive processes play out, methods that are capable of assessing such complex changes will become essential for all family researchers.

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