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RESEARCH BRIEFS

Childbearing Biographies as a Method to Examine Diversity and Clustering of Childbearing Experiences: A Research Brief

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Abstract
Due to increasing heterogeneity in if, when, and under what conditions women have children, the timing, spacing, and other demographic aspects of childbearing have drastically changed in the US over the past century. Existing science tends to examine demographic aspects of childbearing separately, creating an incomplete understanding of how childbearing patterns are distributed at the population level. In this research brief, we develop the concept of childbearing biographies to emphasize that multiple childbearing characteristics cluster together. We analyze nationally representative US data from the 1979 National Longitudinal Survey of Youth (NLSY79; $N=4052$). Using eight childbearing variables (e.g., age at first birth, number of children, whether unmarried at any birth), we use Mixed-Mode Latent Class Analysis (MM-LCA) and identify five classes, or childbearing biographies: (1) early compressed childbearing, (2) staggered childbearing, (3) extended high-parity childbearing, (4) later childbearing, and (5) married planned childbearing. A childbearing biography approach highlights the increasingly heterogeneous contexts of parenthood today, showing how women with similar characteristics around one aspect of childbearing (e.g., early age at first birth) can also be highly divergent from each other when taking into consideration other childbearing characteristics. In showing this complexity, we highlight that a childbearing biography approach has the potential to shed new light on widening inequality among contemporary midlife women, with implications for aging and population health and well-being.

Keywords Family background · Latent class analysis · Motherhood · Childbearing · Second demographic transition

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Introduction

About 85 percent of midlife women in the US are parents (Livingston, 2015), with a significant body of work showing that patterns of childbearing have drastically changed over the past century (Guzzo & Hayford, 2020; Nomaguchi & Milkie, 2020). The current cohort of midlife women has lower parity, older ages at first birth, more nonmarital births, fewer unwanted and mistimed births, and greater congruence between fertility expectations and number of actual births than previous cohorts (Bianchi, 2014; Guzzo, 2021; Livingston, 2019). These shifts constitute a key part of the Second Demographic Transition (SDT) (Zaidi & Morgan, 2017) in which demographic patterns of childbearing have departed from the mid-twentieth century family standardization (Brückner & Mayer, 2005).

To facilitate population research on how childbearing experiences have destandardized among the current cohort of midlife women, we propose a new innovation: the childbearing biography approach. This approach builds on previous studies that identify how multiple childbearing characteristics intersect and cluster together (Hartnett & Margolis, 2019; Johnson et al., 2018), such as research showing later ages of first birth are linked to fewer children generally (Tomkinson, 2019). Understanding how age at first birth and parity patterns further intersect with other childbearing characteristics (e.g., unwanted births, nonmarital births) provides a pathway towards identifying important diversity among women in childbearing experiences that may uniquely shape their overall well-being. In this way, the childbearing biography approach complicates a singular approach to childbearing experiences, offering a more complex and representative view of the contexts in which women have children today.

Our approach builds on two existing approaches: the "marital biography" framework and the concept of "reproductive careers." Drawing on a life course approach which emphasizes that an individual's life events and trajectories unfold over time (Elder et al., 2003), family researchers developed the marital biography approach (Hughes & Waite, 2009). The marital biography is used to show how multiple aspects of marital histories accumulate over time—such as duration of married and non-married periods and marital transitions (McFarland et al., 2013; Reczek et al., 2016). Johnson et al. (2018) created the concept of "reproductive careers," calling for the integration of fertility and infertility experiences over time. Inspired by these perspectives, we develop the childbearing biographies approach, which emphasizes the interconnectedness of multiple demographic aspects of childbearing and considers differences in their prevalence and distribution. In moving beyond individual childbearing variables, we draw attention to the fact that childbearing is an extended process over the life course not easily represented by one or two childbearing characteristics. Understanding the clustering of these childbearing characteristics brings a more appropriate and accurate lens to understanding the prevalence of different demographic contexts of childbearing within the population within the population, with future studies able to build on this and uncover which biographies are associated with multiple types of disadvantages and advantages.

Materials and Methods

We analyze the 1979 National Longitudinal Survey of Youth (NLSY79), a nationally representative cohort study that includes nearly four decades of comprehensive childbearing variables across time (1979–2018) (Rothstein et al., 2019). Our sample includes the 4052 women who have given birth in the sample.

Childbearing Biography Measures

The NLSY79 has comprehensive measures of childbearing histories, including childbearing events that took place prior to the start of the survey and between survey waves. We use these to construct eight childbearing biography variables. This includes three continuous variables—age at first birth, age at last birth (equal to age at first birth if one child), and number of live births—and five dichotomous variables—whether unmarried at any birth, whether had more total children than had expected in 1979, whether any births within 23 months or less of each other, whether any births were "unwanted" at time of birth, and whether any births "mistimed." For unwanted or mistimed births, respondents were asked regarding each pregnancy if just before becoming pregnant wanted to be pregnant. We categorized "No, not at all" as an unwanted pregnancy and "No, not at that time" as mistimed (Guzzo, 2021). We tested models including several other variables, such as pregnancy losses (i.e., miscarriages, stillbirths), abortions, and multiple births (e.g., twins), but these were not included in final models because they did not improve model fit statistics, were very highly correlated with existing variables, or did not add theoretical importance to the existing set of variables. Table 1 shows the size and direction of correlations between each of these childbearing variables (using point biserial correlations for the correlations between continuous and dichotomous variables), with darker colors indicating stronger correlations. These correlations suggest that our

Table 1 Correlation matrix of childbearing biography variables: NLSY79, N = 4052

	Age at first birth	Age at last birth	Number of children	Unmarried for any children	Number of children exceeded expectations (1979)	Less than two years between any births	Any unwanted births	Any mistimed births
Age at first birth	1.00							
Age at last birth	0.60	1.00						
Number of children	-0.37	0.26	1.00					
Unmarried for any children	-0.38	-0.15	0.18	1.00				
Number of children exceeded expectations (1979)	-0.22	0.13	0.56	0.18	1.00			
Less than two years between any births	-0.16	-0.01	0.54	0.07	0.31	1.00		
Any unwanted births	-0.23	-0.01	0.25	0.29	0.19	0.10	1.00	
Any mistimed births	-0.33	-0.10	0.25	0.32	0.18	0.17	0.09	1.00

Darker colors indicate stronger correlations childbearing variables do cluster together in meaningful ways, with each still representing a distinct construct.

Analytic Strategy

We use Mixed-Mode Latent Class Analysis (MM-LCA) to identify the Childbearing Biographies. MM-LCA is a type of Latent Class Analysis (LCA), a person-centered approach that is useful for uncovering and describing patterns and intersections among covarying measures (Morgan, 2015). LCA assumes that values for a set of observed variables (e.g., childbearing characteristics) represent an underlying latent variable with a fixed number of mutually exclusive subtypes or classes (e.g., childbearing biographies) (Collins & Lanza, 2009). With LCA, we are able to identify homogeneous subgroups (e.g., women with similar childbearing biographies) within the larger heterogeneous population (Vermunt & Magidson, 2002). Each case is grouped into only one class, *k*, but each case is also given a probability value of belonging to each of the *k* classes, with these probability values taken to represent the approximate prevalence of each class (Morgan, 2015). With MM-LCA, we are able to use multiple data types as indicators in order to group respondents, including both discrete and continuous data with various parametric distributions (Morgan, 2015; Sammel et al., 1997). One concern with MM-LCA is that one data type might dominate the structure of the latent class models, so we estimate the expected posterior gradient (EPG), which measures the absolute contribution of a variable to MM-LCA, to evaluate this concern (Zhang & Ip, 2014), and we did not find evidence this was the case.

We use model fit statistics, specifically Akaike information criterion (AIC), Bayesian information criterion (BIC), sample size-adjusted Bayesian information criterion (SSBIC), the Vuong–Lo–Mendell–Rubin likelihood ratio test (VLMR LRT), and the parametric bootstrapped likelihood ratio test (PBLRT), to identify optimum numbers of classes (Asparouhov & Muthén, 2014; Jung & Wickrama, 2008; Morgan, 2015; Nylund-Gibson & Choi, 2018)—alongside existing theories and demographic research on childbearing experiences (Guzzo & Hayford, 2020; Nomaguchi & Milkie, 2020). Finally, we estimate the probabilistic assignment of each respondent to each class (e.g., childbearing biography) based on the posterior probabilities estimated in the first step. Analyses are conducted in MPlus (Muthén & Muthén, 2017).

Results

Model Selection

For model selection and evaluation in MM-LCA, we first sequentially fit models, beginning with the one-class model and continuing until the model fit (based on statistical criteria, parsimony, and interpretability) no longer improved (Collins & Lanza, 2009; Morgan, 2015). We estimate 1–10 classes, giving the most credence to

BIC and SSBIC based on recommendations from past simulation studies (Morgan, 2015; Nylund et al., 2007). AIC, BIC, SSBIC, VLMR, and PBLRT for each model are shown in Table 2. We graph AIC, SSBIC, and BIC, identifying the points of "diminishing returns" at the 3-, 5-, and 9-class models. The VLMR LRT and the PBLRT provide a *p* value comparing a *k*-1 class model to a *k* class model. A significant *p* value provides evidence for the *k*-1 class model. Within our estimates, the PBLRT is $p<0.001$ in all test models, and, for the VLMR LRT, the 2–8-class models $p<0.001$. We suggest that these different fit statistics collectively provide the strongest evidence in support of the 3-class or 5-class model. Considering the meanings, parsimony, and class size of the 3- and 5-class models within context of existing research and theory, we identify the 5-class model as preferable because it provides a better overview of the diversity of childbearing experiences among the current cohort of midlife women than the 3-class model (Guzzo & Hayford, 2020; Zaidi & Morgan, 2017). Additionally, entropy values greater than 0.80 suggest "good" classification of individual cases into classes (Clark & Muthén, 2009), and the entropy for the 5-class model is 0.81.

Childbearing Biographies

The item-response probabilities (for the dichotomous variables) and the mean estimates (for the continuous variables) used in construction of the five childbearing biographies as well as the name and expected relative size of each childbearing biography are shown in Table 3. We name these childbearing biographies (1) early compressed childbearing, (2) staggered childbearing, (3) extended high-parity

Table 2 Fit statistics: childbearing biographies (NLSY79; $N=4052$)

Number of Classes	AIC[a]	BIC[b]	SSBIC[c]	VLMR LRT (p)[d]	PBLRT (p)[e]
1	89,946.65	90,016.03	89,981.08		
2	86,475.86	86,602.00	86,538.45	<.001	<.001
3	83,887.52	84,070.43	83,978.28	<.001	<.001
4	83,031.17	83,270.84	83,150.10	<.001	<.001
5	82,228.84	82,525.28	82,375.93	<.001	<.001
6	81,632.37	81,985.57	81,807.63	<.001	<.001
7	81,113.42	81,523.39	81,316.85	<.001	<.001
8	80,706.93	81,173.67	80,938.53	<.001	<.001
9	80,358.33	80,881.83	80,618.09	0.112	<.001
10	80,153.96	80,734.23	80,441.89	0.062	<.001

[a]Akaike information criterion

[b]Bayesian information criterion

[c]Sample size-adjusted Bayesian information criterion

[d]Vuong–Lo–Mendell–Rubin likelihood ratio test

[e]Parametric Bootstrapped likelihood ratio test

Table 3 Item response probability and means/standard deviations for childbearing biography indicators used in latent class analysis and expected sample size (NLSY79; $N=4052$)

	Early compressed childbearing	Staggered child-bearing	Extended high-parity childbearing	Later childbearing	Married planned child-bearing
Expected *n*	1147	1087	146	421	1251
Expected %	28.3%	26.8%	3.6%	10.4%	30.9%
Mean					
Age at first birth	19.5 (0.2)	19.6 (0.2)	18.4 (0.5)	34.3 (0.6)	26.5 (0.4)
Age at last birth	22.8 (0.3)	29.4 (0.4)	33.2 (0.8)	36.4 (0.3)	30.5 (0.4)
Number of children	1.8 (0.0)	3.4 (0.1)	6.0 (0.4)	1.7 (0.1)	2.0 (0.1)
Probability of					
Unmarried any child	.56	.67	.77	.22	.16
More children than expected in 1979	.11	.70	.94	.16	.18
Less than two years between any births	.14	.55	.93	.18	.16
Any unwanted births	.20	.38	.53	.11	.07
Any mistimed births	.56	.74	.77	.18	.28

childbearing, (4) later childbearing, and (5) married planned childbearing, with these names based on the most salient and distinguishing characteristics of each group. The largest childbearing biography, married planned, represents about 31 percent of the sample. Women within this biography generally have their children in their mid-20s to early-30s, have about two children, and have lower rates of being unmarried at any births and any unwanted births than other biographies, as well as low rates of childbirth within two years, low rates of having more children than expected, and low rates of any mistimed births. The later biography (10% of sample) has many childbearing characteristics in common with the married planned biography, including low rates of having more children than expected, low rates of any childbirths within two years, and low rates of any unwanted or mistimed births. In contrast to the married planned biography respondents, the later biography has the oldest ages of first and last birth (34.3 and 36.4 years, respectively) and the fewest children (mean: 1.7).

The early compressed biography respondents (about 28% of the sample), similar to the later biography respondents, also has a relatively short childbearing duration (about 3.3 years, compared to 2.1 years for later biography), less than two children on average, and low rates of having more children than expected, low rates of fewer than two years between births, and low rates of any unwanted births. But in contrast to married planned and later biographies, the early compressed biography respondents have much younger ages of first and last birth (late adolescence through early 20s). Additionally, about 56 percent of respondents in this biography are unmarried for at least one birth and have at least one birth characterized as mistimed.

The remaining two childbearing biographies are distinct from these first three. Similar to the early compressed biography, women in both the staggered and extended high-parity biographies have their first birth in late adolescence (19.6 and 18.4 years, respectively) and high rates of any unmarried births and any mistimed births. But, in contrast to early compressed, both also have high rates of more children than expected and less than two years between births. The extended high-parity biographies (least common group, comprising only about 4% of the full sample) have higher rates of each of these characteristics than the staggered biography, as well as the highest rates of any unwanted births (53%). For example, 94 percent of respondents within the extended high-parity biography have more children than expected and 77 percent have any mistimed births, and this group has the most children—6.0 on average and the longest childbearing duration (about 14.8 years). The staggered biography represents 27 percent of the sample. Respondents within this biography have almost half as many children on average as the extended high-parity biography (3.4, on average) and a younger mean age of last birth (29.4 years).

Discussion

Understanding if, when, and under what conditions people have children and the prevalence of these different childbearing patterns are useful innovations in our demographic and life course understanding of fertility. A childbearing biography approach emphasizes the interrelations and systematic patterning of multiple childbearing characteristics, with our findings demonstrating five distinct childbearing biographies most common among midlife women in the US today: (1) early compressed childbearing, (2) staggered childbearing, (3) extended high-parity childbearing, (4) later childbearing, and (5) married planned childbearing.

Overall, our childbearing biography approach provides evidence that experiences of childbearing are de-standardized, yet still clearly patterned in meaningful ways (Brückner & Mayer, 2005). Importantly, no single childbearing biography statistically dominates the sample but rather three biographies—early compressed, staggered, and married planned—are similar in prevalence, each comprising over one-fourth of the total sample. These biographies are fairly distinct from each other in some ways (e.g., almost three times as many women with staggered biographies have any mistimed births compared to women with married planned biographies) and overlap in other ways (e.g., early compressed and married planned both have about two children), representing distinct clusters of childbearing characteristics. The prevalence of these biographies, alongside the less common extended high-parity biography and later biography, demonstrates the diversity of childbearing patterns within this cohort of midlife women, while still identifying that some childbearing patterns are more common than others.

As a second example regarding de-standardization, although about one-fourth of the sample had their first child before the age of 20, the childbearing biographies of women with adolescent births are quite diverse. In fact, we find three unique childbearing biographies that include adolescent childbirth (early compressed, staggered, and extended high parity). By demonstrating that adolescent birth is not a monolithic experience but rather varies in form across other dimensions of childbearing, we provide evidence against the erroneous notion of a universal experience of teenage motherhood. Our approach draws attention to the possibility that adolescent births (as well as nonmarital births, high parity, and closely-spaced births, among other childbearing characteristics) are not necessarily disadvantageous on their own, in support of other studies (Carlson & Williams, 2011; Rackin & Brasher, 2016). We suggest that different childbearing contexts *around* and *stemming from* adolescent births (or any other individual childbearing characteristic) matter for the meaning and implications of those experiences.

This research brief aims to provide an overview and empirical demonstration of the childbearing biography concept, and we contend that this concept has innovative potential across many different areas within demography. For example, future research using the childbearing biography approach should document characteristics of the women comprising each biography to examine whether some women (e.g., low-income women) cluster in certain biographies and to track changes in the prevalence of these biographies and their covariates across cohorts. As another example, a childbearing biography approach offers a method in estimating associations between childbearing patterns and life chances across the life course, including mental and physical health, health behaviors, employment, and socioeconomic opportunities (Augustine, 2021; Wolfe, 2009). Given the centrality of childbearing experiences to later-life outcomes (Nomaguchi & Milkie, 2020; Thomas & Thomeer, 2019), this approach could also better illuminate disparities far beyond childbearing years, including financial, physical, mental, relational, and emotional well-being. Previous research identifies that women with adolescent births have more later-life health issues and higher risks of early mortality (Henretta, 2007; Patel & Sen, 2012), and the childbearing biography approach has the potential to add context to this persistent finding, showing how adolescent births operate alongside other childbearing measures to matter for long-term well-being. Finally, although we limit our analysis to eight childbearing characteristics, future analysis could expand this concept to include multiple other childbearing (and non-childbearing) measures, including pregnancy losses and contraception use, as well as other family and relationship variables (Grundy & Read, 2015; Johnson et al., 2018).

Taken together, the childbearing biography approach provides key information about how childbearing patterns are distributed within the population, moving us beyond understandings of childbearing demonstrated by one or two indicators. Our approach can spur more comprehensive research on contemporary (and historical) demographic patterns of childbearing, with implications for future examinations of the impact of different childbearing biographies on health, well-being, and inequality in the US today. The potential of the childbearing biography approach lies in its ability to illuminate how childbearing "choices" are patterned and constrained, providing useful new evidence on the stratification of childbearing.

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