To Grandmother's House We Go: Informal Childcare and Female Labor Mobility*

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February 29, 2024

Abstract

We study how childcare costs and the location of extended family influence the labor supply and mobility of U.S. women. We observe women returning to their home locations immediately before fertility events, suggesting that the desire for informal childcare is a motivator of home migration. Moreover, women who live nearby their parents have lower child earnings penalties. We then build a dynamic model of labor supply and migration to assess the impacts of counterfactual policies. We find that childcare subsidies increase earnings and mobility among U.S. women and that ignoring migration can understate the welfare benefits of these policies considerably.

Keywords: Migration, childcare, female labor supply, human capital.

*We thank John Kennan, Corina Mommaerts, Rebecca Lessem, Jeff Smith, Chris Taber, Matt Wiswall, Ronni Pavan, Theodore Papageorgiou, Tatiana Homonoff, Maria Fitzpatrick, Briana Ballis, Audrey Guo, Catherine Michaud-Leclerc, Yiwei Zhang, and seminar participants at the University of Wisconsin-Madison, Boston College, University of Rochester, University of Nebraska-Lincoln, University of Pennsylvania, Arizona State University, and SOLE for helpful feedback. We are also grateful to Edoardo Bella for excellent research assistance. Additionally, this material is based upon work supported by the National Science Foundation Graduate Research Fellowship Program under Grant No. DGE-1747503. Any opinions, findings, and conclusions or recommendations expressed in this material are those of the authors and do not necessarily reflect the views of the National Science Foundation. Support was also provided by the Graduate School and the Office of the Vice Chancellor for Research and Graduate Education at the University of Wisconsin-Madison with funding from the Wisconsin Alumni Research Foundation. All remaining errors are our own.

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1 Introduction

How does childcare availability influence the labor force attachment and migration behavior of women in the United States? The cost of childcare in the United States is often a financial hardship for families: recent surveys indicate that the average cost of center-based infant care exceeds 27 percent of median income for single parents [Child Care Aware, 2017]. An alternative to high-cost private care is to use relative-based care, but this option can only be used if relatives are nearby. Thus, childcare needs may constrain both the labor force *participation* and the geographic labor *mobility* of U.S. women.

The goal of this paper is to study how migration choices are constrained by childcare needs and the implications for these location constraints for women's earnings. We first show that women are 33% more likely to move back to their birth state directly prior to their first birth and that women with children exhibit considerably stronger labor force attachment when living in their home state. We then use panel data from the Panel Study of Income Dynamics to analyze how the child earnings penalty varies based on proximity to the child's grandparents and local childcare costs. We show that women who give birth less than 25 miles from their own parents experience a substantially smaller child earnings penalty than women who have a child elsewhere. Additionally, a one-standard deviation increase in the average weekly price of childcare at the county-level increases the child penalty by $2,329 or 11 pp.

These descriptive facts motivate the construction of a structural model to test how additional childcare subsidies would alter women's migration and working decisions. Typically, analyses of the impacts of childcare subsidies focus on the direct impacts of such subsidies on labor force participation and human capital accumulation as the primary mechanism through which such subsides impact women's earnings.[1] However, if the high costs of non-subsidized childcare prevent households from moving far from their parents and thus from optimally sorting across labor markets, we might expect that there is a secondary effect on earnings and welfare stemming from reduced frictions in labor mobility.

We therefore explore these mechanisms in a model that nests a canonical model of dynamic labor force participation in a model of dynamic migration. Each period, women choose their fertility status, labor force attachment, and where to live. Mothers must balance the trade-off between building experience through labor force participation and paying more in

[1] For an overview of the literature on the elasticity of women's labor supply to childcare costs, see [Del Boca, 2015].

childcare costs, though if they live in their parent's location, they receive a portion of free childcare. We estimate considerable racial heterogeneity in informal care usage, and counterfactual simulations indicate that fully subsidizing childcare would increase women's lifetime wages by 10% overall. The policy also increases the total number of moves made over the lifecycle by 3 percent and particularly increases moves over non-home locations. Finally, the ability to move to higher utility locales has a meaningful role in influencing the welfare gains from childcare policies: compared to our baseline simulation, willingness-to-pay for a full childcare subsidy is over 7 percent lower in an alternate model where moving is prohibited and over 12 percent lower for women who in baseline have an informal care option available to them.

Our paper expands upon and ties together three broad areas of research: the literature on childcare costs and women's labor force participation, the literature on the determinants of migration, and the literature on the implications of family-based ties for labor market outcomes.

First, our paper introduces a new mechanism that contributes to the 'child penalty' faced by mothers: increased job mobility frictions caused by location-specific childcare access. Past research shows that women experience large earnings drops following the birth of a child [Kleven et al., 2019b, Cortes and Pan, 2020, Goldin and Mitchell, 2017, England et al., 2016, Gangl and Ziefle, 2009, Budig and England, 2001]. One possible explanation for the dip in earnings post-birth is that women reduce work hours due to high costs of childcare. Analyses of free or subsidized childcare in Canada [Baker et al., 2008, Lefebvre and Merrigan, 2008], Europe [Bauernschuster and Schlotter, 2015, Bettendorf et al., 2015, Lundin et al., 2008], and the United States [Cascio, 2009, Tekin, 2007, Bainbridge et al., 2003, Blau and Tekin, 2007, Borowsky et al., 2022, Landivar et al., 2022] indicate that such programs increases the likelihood that women work, while also crowding out their use of informal care.[2] We argue, however, that this substitution away from informal care is also a mechanism through which these subsidies may improve women's labor market prospects. By allowing women to no longer rely on relative care, they are able to be more mobile and potentially achieve welfare gains by moving to a more productive labor market than their parents live in or to a better job match.

Our analysis of child penalties is most similar to Kleven et al. [forthcoming] and Karademir et al. [2023], which study how child penalties vary with childcare costs in Austria

[2]Recent papers find more limited impacts of childcare subsidies on employment, possibly due to this crowd-out Fitzpatrick [2010], Havnes and Mogstad [2011].

and Canada respectively. Kleven et al. [forthcoming] use variation over time and geography in nursery and kindergarten childcare to show that sudden, unanticipated increases in the number of available childcare seats have no significant impact on the child penalty in the years following a birth. Karademir et al. [2023] explore childcare in the context of grandparent proximity, finding that women are more likely to live close to their parents following their first birth and that the child penalty is 4 p.p. smaller for women living in the same Canadian Census Division as their parents. Our paper contributes to this literature by exploring these questions in the context of the United States, which has uniquely high prices of childcare and low levels of government support for parental leave and childcare relative to Canada and European countries. We find much larger impacts of both proximity to grandparents (20 p.p. difference) and accessible childcare on the child penalty (11 p.p. difference) than both of these papers, possibly due to the greater burden of childcare costs in the United States.

Additionally, we build upon a long-standing strand of the women's labor participation literature which considers how childcare would change women's labor force participation decisions throughout the life cycle rather than just in the immediate aftermath of policy implementation as in the prior papers. Our model builds directly on the frameworks of dynamic labor supply in presence of fertility seen in Eckstein and Wolpin [1989], Francesconi [2002], Bick [2016], and Adda et al. [2017]. We extend these models by incorporating informal care from family and migration decisions. By incorporating these components, we are able to show that while the majority of the welfare gains women accrue from childcare subsidies are from increased labor force participation, about one-tenth of the gains are attributable to women being able to sort into their preferred labor markets.

Second, our model also contributes to our understanding of the factors influencing return migration and home-biases in location choices. Older work has studied repeated and return migration [Davanzo, 1983, Dierx, 1988] with the view that such moves are driven entirely by monetary influences. Some more recent work [Diamond, 2016, Kennan and Walker, 2011, Bishop, 2008] considers non-monetary factors agents weigh when making repeated moving and location choices, but these papers typically condense preferences for living in one's home location into a single utility premium. A small literature has documented the role of emotional attachment to places' characteristics and the role of concentration of extended family in location decisions [Boyd et al., 2005, Spilimbergo and Ubeda, 2004, Zabek, 2019, Spring et al., 2017]. Through focusing on fertility as a new driver of home migration, we aim to further unpack the specific determinants of return migration and add to the literature that studies how individuals balance pecuniary and non-pecuniary factors when making migration decisions in the United States.

Lastly, our paper incorporates migration decisions into the growing literature on the implications of family-based ties for labor market outcomes. Proximity to family can mitigate child or elder care needs, allowing greater attachment to the labor force. Geographic distance from one's mother or mother-in-law is associated with a greater likelihood of childcare transfers, allowing for higher labor force participation for women [Compton and Pollak, 2015, 2014, Chan and Ermisch, 2015]. To identify the effects of access to grandparent care, past research has used variation in pension generosity and retirement age [Dimova and Wolff, 2011, Aparicio-Fenoll and Vidal-Fernandez, 2015, Zamarro, 2020, Bratti et al., 2018, Posadas and Vidal-Fernandez, 2013] and the death of grandparents [Arpino et al., 2014, McMurry, 2021] to show that larger grandparent time transfers are associated with higher earnings for mothers. Beyond the realm of childcare, co-location near parents acts as a buffer against earnings losses for adult children following a job displacement [Coate et al., 2017, Kaplan, 2012].

To our knowledge, the only other paper that assesses the interaction of informal childcare and migration choices is García-Morán and Kuehn [2017], who build a model of residence choice, fertility decisions, and female labor force participation in the context of Germany. Our contribution relative to their paper comes from our focus on dynamics: the authors model migration, working, and fertility decisions as one-shot choices. However, labor force participation and migration are dynamic processes: multiple moves and return migration are salient features of the data [Kennan and Walker, 2011]. Because we allow for dynamic location choices, our framework will capture the life-cycle implications of childcare policies.

The paper is organized as follows: Section 2 motivates our research question by providing descriptive evidence regarding the timing of home migration and fertility events observed in U.S. data. Section 3 details our model, and Section 4 describes our estimation procedure. Section 5 presents model estimates and evaluates the model's fit, while Section 6 presents the results of counterfactual simulations. Finally, Section 7 considers potential avenues for future research before concluding.

2 Motivation

In this section, we present empirical evidence that U.S. women's location choice is responsive to childcare needs and that women's labor market outcomes following their first birth are tied to proximity to their child's grandparents.

2.1 Fertility and Return Migration among U.S. Women

The high cost of childcare in the United States may compel woman with small children to make different location and working decisions than those without. In particular, we may expect women with young children to be more likely to move back to their parent's location to take advantage of familial support in raising children and for women with children to work more hours if their parents are in their same location than if not. Women with small children should also be more reluctant to move to locations with higher childcare costs than those without, other things equal.

To test these hypotheses, we use data from the 2006-2019 waves of the American Community Survey (ACS) [Ruggles et al., 2020]. Each year of the ACS contains a 1 percent sample of the entire United States' population, providing a large number of observations. Additionally, the 2006-onward waves of the ACS also contain information on one-year migration histories. This information, coupled with extensive demographic information and state-level measures of childcare costs, will allow us to observe some simple margins of behavior that the presence of young children influences.

We restrict our ACS sample to women aged 22-40 who were born in the United States. We drop individuals who did not complete at least one year of high school education. The women in our sample are limited to those who are coded as household heads, spouses of household heads, or children/children-in-laws of household heads (to allow for the possibility of "boomerang migration," or individuals moving back into their parents' home). The ACS additionally records the youngest own child for all respondents, allowing us to distinguish women who have young children from those who do not. We exclude observations whose age and age of youngest child imply a birth before the respondent was age 14.

We supplement this data with data on childcare prices sourced from the US Department of Labor's National Database of Childcare Prices (NDCP) which provides county by year level data on center-based and in-home childcare costs for 2008-2018. We measure childcare costs as the median weekly price of toddler center-based care, aggregated to the state-level as the population-weighted mean across counties. For a visual representation of average full-time toddler childcare expenses across U.S. census divisions, refer to Figure A.1a.

We first investigate whether women are more likely to move home in response to fertility events. We restrict our sample to women who were not living in their or their husband's state of birth in the year before the interview and then run the linear probability model:

$$h_{it} = \beta_0 + \boldsymbol{\beta}_1 \boldsymbol{X}_{it} + \beta_3 f_{it} + \tau_t + \varepsilon_{it},$$

where h_{it} indicates whether individual i moved back to their or their husband's birth state in year t. $\boldsymbol{X}_{it}$ contains a vector of demographic controls as well as birth place, state of residence, and previous state of residence fixed effects, τ_t are year fixed effects, and f_{it} indicates individual i's first fertility status in year t, defined by presence of a child belonging to the respondent that is less than 1 year old while also being the only child of the respondent in the household. Standard errors are consistent under heteroskedasticity, and regressions are weighted using sampling weights provided by the ACS. We focus on the first pregnancy because the presence of additional children may make migration more cumbersome — thus, women may be more likely to move home in response to their first fertility event than subsequent ones. We run our specification for all women as well as for non-married (including never married, divorced, separated, and widowed) and married women separately, as having two potential earners in the household may make married women less likely to move in response to fertility than single women. We also run the specification separately by race.

Table 1 reports the results of this exercise. We find that initial fertility events make women 33% more likely to home-migrate. These effects are also much stronger for single women than married women, and we can reject the null that the effects are equal across groups in a t-test of equality of coefficients. Initial fertility events make single women roughly 60% more likely to move home compared to the rest of the sample off a base rate of 3.3 percent, whereas married women's likelihood increases by only 19%. We also find that there are significant differences by race, with White and Black mothers being more likely to move back home than those who are neither White nor Black. When we look fertility patterns for different types of women in Appendix Table A.1, we see that, compared to non-movers in the home location and women who stay in non-home locations, women who have moved back home in the previous year (A) have fewer children, (B) have children who are on average 1.2-1.4 years younger, and (C) are 1.6 p.p. more likely to have had their first birth in the last year.

The variation captured in this regression can also be presented visually: in Figure 1, we plot rates of home migration for women with only one child in the ACS, broken up by the age of their child and marital status. We see a larger spike in home migration for unmarried women with a newborn than for married women, and the increase in migration rates does not extend to older ages, perhaps due to increased costs of migration when children are present as opposed to merely impending. Similar patterns hold when looking at mothers of multiple children and the age of their eldest child, though the decline in migration at older ages is less steep. However, when we look at the likelihood of moving as a function of later births

Table 1: Effects of First Pregnancy on Home Migration Probability (HMP)

	(1) All Mean = 3.57	(2) Non-Married Mean = 3.29	(3) Married Mean = 3.84	(4) White Mean = 3.70	(5) Black Mean = 3.24	(6) Other Races Mean = 3.52
First Pregnancy (FP)	1.179***	2.072***	0.783***	1.403***	2.051**	-0.313
	(0.186)	(0.426)	(0.203)	(0.216)	(0.666)	(0.405)
Observations	933,489	441,608	491,881	707,994	94,990	105,107
R-squared	0.051	0.049	0.061	0.058	0.079	0.125

Notes: The sample includes US-native-born women aged 22-40 in the 2006-2019 ACS who completed at least one year of high school and were not located in birth state or birth state of their husband if married the previous year. Additional controls include fixed effects for birth state, current state, and previous state, and calendar year, a quadratic in age, indicators for education (HS drop out (omitted), HS, Some College, College, More than College), indicator for marital status, and indicators for race (White (omitted), Black, Non-White/Black). First pregnancy indicator defined by presence of a child less than one year old while being the only own child of the respondent in the household. Regressions weighted by sampling weights and robust standard errors in parentheses.$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

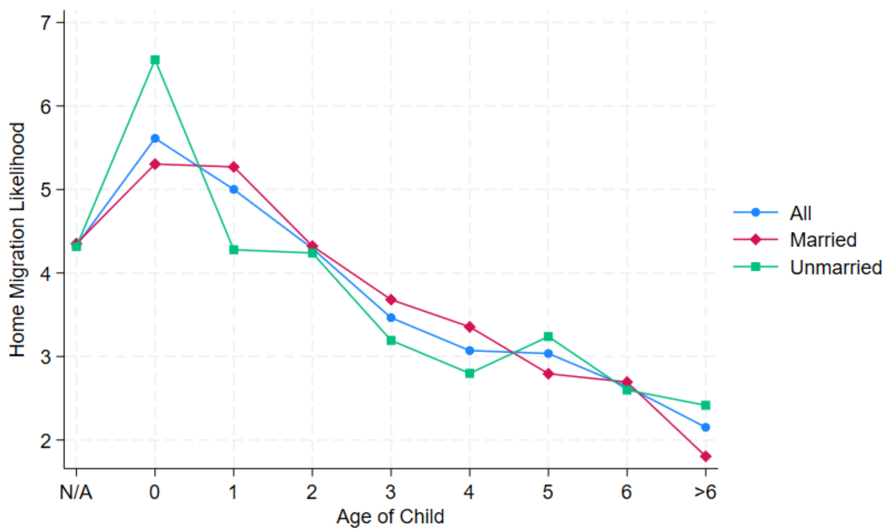
(Appendix Table A.2), there is no effect of later pregnancies on likelihood of a move.

Do women who choose to move home at time of their first pregnancy differ in observables from women who stay in a non-home state location? Table 2 reports the demographic characteristics of women who are living in their or their husband's home state in the year prior and post first-birth (col. 1), women who move back to their or their husband's home state (col. 2), and women who are not living in their or their husband's home state following a birth. Women who choose to move home are younger, less likely to be married, less likely to have a college degree, and have lower personal and family income than women who choose to stay in their home state. Notably, while women outside of their birth state have higher personal and family income than women who are living in their birth state, non-mover women[3] that live in the home state are more likely to be working post-birth, though they had similar rates of full-time employment pre-birth. This is consistent with a story in which women who are less resourced and able to afford the costs associating with having children are more likely to move home, and those who are living in their home state have access to familial and social networks that allow them to stay attached to the workforce.

We next investigate whether the presence of young children is associated with moving to a lower childcare cost destination. We limit our ACS sample to women who are observed to have moved from their previous-year state and have not moved to their state of birth.

[3]Due to the disruption of a recent move to employment, comparing movers to non-movers will likely misstate the relationship between birth state and employment status, thus we compare always stayers in birth vs. non-birth states.

Figure 1: Home Migration Rates by Age of Child



Notes: Sample is US-native women aged 22-40 in the 2006-2019 ACS who completed at least one year of high school, have one or fewer children, and were not located in their or their husband's birth state the previous year. N/A indicates that observation in data has no children in household.

We then test whether the presence of young children results in women being less likely to locate in high childcare-cost states, by regressing the NDCP's average weekly cost of center-based child-care for toddlers in the destination location on an indicator for having a child under the age of five. Table 3 presents the results of this test and affirms the hypothesis — moving women with young children on average choose to locate to states with lower childcare costs than those without, with the effects again being noticeably stronger for single women than married ones. Single female movers with young children move to states with about 2.2% lower childcare prices than single female movers without children, and married women move to states with 1.1% lower childcare prices. Childcare prices are also lower in destination locations for non-White and non-Black households in particular (3% lower than mean), consistent with the previous finding that non-White and non-Black households are less likely to move home where they could use relative care.

Finally, we investigate how location and the presence of children influence the labor force attachment of women in the ACS. We regress usual hours worked per week in the previous year on a variety of covariates to do with the presence of children, location, childcare costs, and marital status. Intuitively, higher childcare costs ought to decrease hours worked by

Table 2: Characteristics of Women in Year Following First Birth

	Non-Mover, Home	Mover, Home	Non-Home	All
Age	28.56	27.91	29.72	28.83
	(4.376)	(4.485)	(4.744)	(4.506)
White	0.748	0.815	0.768	0.755
	(0.434)	(0.389)	(0.422)	(0.430)
Black	0.104	0.0895	0.0905	0.100
	(0.305)	(0.286)	(0.287)	(0.300)
Married	0.739	0.749	0.756	0.744
	(0.439)	(0.434)	(0.430)	(0.437)
College	0.307	0.293	0.328	0.312
	(0.461)	(0.455)	(0.469)	(0.463)
Currently Employed	0.743	0.553	0.698	0.725
	(0.437)	(0.497)	(0.459)	(0.447)
Worked Full-Time, Prev. Year	0.563	0.494	0.568	0.562
	(0.496)	(0.500)	(0.495)	(0.496)
Family Income, Prev. Year	88820.8	92027.5	102768.8	92301.4
	(76973.5)	(84769.2)	(96817.3)	(82848.8)
Own Income, Prev. Year	32061.5	26716.5	37781.8	33314.9
	(35939.8)	(38669.4)	(46545.9)	(39036.3)
Observations	67,930	1,504	24,153	94,543

Notes: This table reports mean and s.d. (in parentheses) of demographic characteristics of US-native women aged 22-40 in the 2006-2019 ACS who completed at least one year of high school and have a child less than one year old which is the only own child of the respondent in the household. Col. 1 includes women living in their birth state in the prior and current year. Col. 2 includes women living in a non-birth state in the prior year and in their birth state in the current year. Col. 3 includes women living in a non-birth state in the prior and current year. Col. 4 includes all women in the sample.

Table 3: Effects of Children on Child Care Costs in Destination of Move

	(1)	(2)	(3)	(4)	(5)	(6)
	All	Non-Married	Married	White	Black	Other Races
	Mean = 172.8	Mean =175.3	Mean = 170.1	Mean = 172.4	Mean = 164.3	Mean = 181.7
Young Child	-2.469***	-3.962***	-1.943**	-2.092**	-2.618	-5.721**
	(0.616)	(1.156)	(0.731)	(0.700)	(1.886)	(1.847)
Observations	53,546	26,103	27,443	42,202	4,166	5,772
Adjusted R^2	0.173	0.191	0.155	0.175	0.177	0.160

Notes: The regression outcome is childcare cost, defined as average weekly cost for center-based care for toddlers. The sample includes US-native-born women aged 22-40 in the 2006-2019 ACS who completed at least one year of high school and who moved in the previous year and not to their or their husband's state of birth. Additional controls include fixed effects for birth state, previous state, and calendar year, a quadratic in age, indicators for education (HS drop out (omitted), HS, Some College, College, More than College), indicator for marital status, and indicators for race (White (omitted), Black, Non-White/Black). Young child defined as presence of own child aged at most four in household. Regressions weighted by sampling weights and robust standard errors in parentheses.$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

women because it makes working relatively more expensive. Being proximal to parents ought to increase labor force attachment if parents primarily provide time transfers in child-rearing. Appendix Table A.3 presents the results of this exercise. The presence of children decreases usual weekly hours worked by women substantially, and the effects are noticeably stronger for married women. However, women who have children in their birth state work more than women who do not, while women with children in states with higher childcare costs also working relatively less.

2.2 Grandparent Proximity and the Child Penalty

While our analyses using ACS data provide a snapshot that suggests young children having influence on household location choices, cross-sectional data cannot tell us the long-term impacts of living near relatives or living in low childcare cost regions on women's lifetime earnings trajectory. It is well-documented that women experience a decline in earnings following births, often referred to as the 'child penalty,' which persists for up to ten years post birth [Kleven et al., 2019b]. A large factor in the decline in earnings is women's withdrawal from the labor market. Therefore, we might expect that having access to cheaper or free childcare would allow women to work more hours and reduce the child penalty.

To test this, we use data from the Panel Study of Income Dynamics (PSID) to estimate the size of the child penalty for women living near or far from grandparent care and for women living in high vs. low childcare cost regions. We adopt a modified form of the event study specification first proposed by Kleven et al. [2019b]. For each mother in the data, we define event time (t) based on the year of their first child's birth. Our outcome of interest is person i's earnings Y_{icst} in year s, event time t, and location c where location is county-state. The regression is as follows:

$$Y_{icst} = \sum_{j \neq -2} \alpha_j^g \mathbb{1}[j = t] + \beta_k^g \mathbb{1}[k = age_{is}] + \gamma_s^g + \theta_c^g + X_{it}' B^g + \epsilon_{icst}. \tag{1}$$

The regression contains event-time dummies with α coefficients, age dummies with β coefficients to control for life-cycle trends, year dummies with γ coefficients to control for time trends, location-year fixed effects, θ_s, to control for county-specific time trends, and demographic controls X_{it} which include dummies for race and education. Event-time $t = -2$ is omitted, so all estimates are relative to the year just prior to birth. All coefficients vary by gender; in our primary specification, men who had a child as a comparison group, relying on the fact that past papers show that men do not experience the same disruption in income at the time of their first child. We are able to identify effects of all three sets of dummies because of the variation in the age at which women have children.[4] In a secondary specification, we also use a sample that only contains women; the α terms in these specifications thus represent the difference in earnings for a woman of age k in year s who had a child relative to a woman of the same age in the same year who did not.

The parameters of interest are the α parameters, but they will represent differences in levels. To transform them into percent changes, we calculate $P_t = \frac{\hat{\alpha}_t}{\mathbb{E}[Y_{ics,-2}]}$, where the bottom of the fraction is the mean pre-period baseline earnings in the period two years prior to birth.

We estimate this regression separately for women living near or far from the child's grandparents as well as separately for women living in counties with high or low childcare prices. For this analysis, we need a panel of income data for women in the years surrounding their first birth. To create this, we use the geocode restricted PSID's full retrospective history of births and adoptions, which provides the full history of births for those interviewed in the years 1985 onward. We create a data set including the year women's first birth occurred, their age at that birth, and whether they were married at the time of that birth. Following the restrictions used by Kleven et al. [2019a], the panel includes five years pre-birth and ten years post-birth. We restrict the sample to women who had a birth between the ages of 20 and 40 to abstract away from teenage motherhood. Women are also excluded from the sample if they are missing more than 8 years in this period, missing all years pre-birth, or all years post-birth. We then combine this data with information from the PSID family files on earned income in each year of the women's life, the US county they live in each year, and the US county that their parents live in each year. Because we only observe parents of the PSID respondent, households' grandparent status is based on the location of the parents of whichever spouse has an identifiable parent ID.

To compare child penalties across groups, our statistic of interest is the child penalty gap:

$$\frac{\hat{\alpha}_t^1}{\mathbb{E}[Y_{ics,-2}^1]} - \frac{\hat{\alpha}_t^2}{\mathbb{E}[Y_{ics,-2}^2]}$$

where 1 indicates living in the location that is presumed to have lower costs of childcare (near grandparents, low childcare prices) and 2 indicates the opposite. If these lower costs make it easier for women to stay attached to the labor force, we would expect this gap to

[4] For more details on the identification assumptions needed to assume these are the causal impacts of childbirth, see Kleven et al. [2019b].

be positive indicating that women with access to lower costs childcare have smaller earnings losses post-birth. We use the Delta method to calculate standard errors of this gap and then test whether we can reject the null that the child penalty is equal across types.

Our outcome, earned income, is defined as the reported total income including wages and other income and combines impacts of births on both labor supply and wage.

Note that these estimates should not be interpreted as the causal impact of living near a grandparent or in a childcare cost region on the child penalty. We expect that women are sorting across these locations in part based on their attachment to the labor force; women who want to continue working after a birth for reasons unobservable to us as econometricians are more likely to settle in places with affordable childcare, whether that be relative care or cheaper private care options. We cannot separate these indirect selection effects from the direct effects of having cheaper childcare available. To address differences in pre-birth observables by location, we use inverse probability weighting based on age, race, education, marital status, and pre-birth earnings, following the methods in [Kleven et al., forthcoming] and [Karademir et al., 2023].[5] While this weighting addresses differences in pre-birth observables, such as as the fact that those living in the grandparent's location earn less pre-birth than those living afar, we cannot fully control for selection on unobservables. Nonetheless, these patterns will provide suggestive evidence of whether childcare cost factors are meaningfully related to the long-term child penalty women face following their first birth and motivate the need for a structural model which explicitly models these selection patterns.

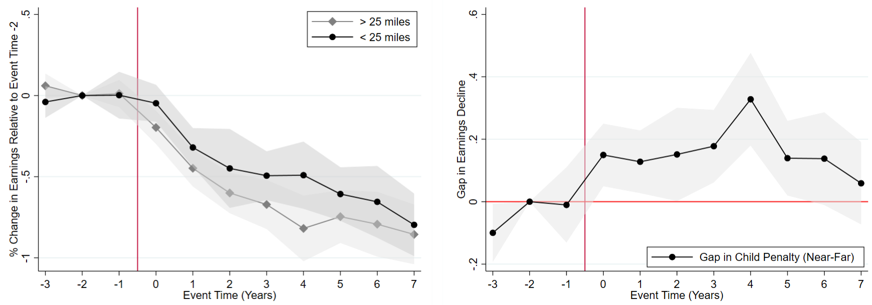
Figure 2 plots the coefficients from the event studies described in Equation 1, with panel A plotting the coefficients separately for mothers who live in the same county as the child's grandparents or in a county whose population centroid is less than 25 miles from the centroid of the county of the child's grandparents (near) or more than 25 miles from the county and panel B plotting the size of the gap between these groups. While both types of mothers experience a large child penalty, those living distant from the child's grandparents experience a child penalty that is about 20 percentage points larger than the child penalty for living close to the grandparents.

Table 4 reports the results of regressions which aggregate the coefficients into post-period, year of birth, and pre-period (excluding two years prior to birth). In these regressions, we vary our definition of 'near' to test that our results are not sensitive to distance or geography

[5] Specifically, we use a Probit model to predict the likelihood π of living within 25 miles of the grandparent's county (in high cost county) as a function of log earnings in the year prior and two years prior to pregnancy, age, race dummies, education dummies, and a dummy for marital status, and we then weight those who live near grandparents (in high cost) $\frac{E[\pi]}{\hat{\pi}}$ and those far from grandparents (in low cost) by $\frac{E[1-\pi]}{1-\hat{\pi}}$.

Figure 2: Child Penalty for Women Living Near or Far from Grandparents

Panel A | Panel B



Notes: Figure 2A (left) plots coefficients and 95% confidence intervals from event studies of earnings on indicators for years surrounding a woman's first birth for both women who live less than 25 miles from their grandparent's counties (near) or more than 25 miles (far). The unit are percent changes (0 to 1) in earnings relative to two years prior to birth. The regression includes men as a control group and includes controls for age of mother at first birth, year of birth, and county time trends. Figure 2B (right) calculates the gap for those near vs. far and reports 90% confidence intervals for a test of the null that this gap is equal to zero.

cutoffs. Panel A reports results for our primary specification in which we include the male control group; Panel B reports results for the regression including only women. Columns 1 and 2 report the coefficient α_1 for the regression of women's labor income on the post-period separately for those living in the same county and those living in the different county as the child's grandparents. While women who live in different counties from the grandparents earn approximately \$20,510 or 78% per year less post-birth, women who live in the same county only earn \$13,521 or 56% less. This translates to a child penalty that is 22 p.p. greater for mothers 'far' from grandparents relative to baseline pre-birth earnings compared to the child penalty for those near grandparents.

As we add more stringent distance requirements, such as being in a different county and more than 25 miles away (column 3), being in a different state (column 4), or being in a different state and more than 25 miles way (column 5), the child penalty grows in magnitude. Columns 6-8 show the difference in the child penalty for difference distance bins; as before, the child penalty is larger relative to baseline as the distance radius from grandparents increases. In our secondary specification omitting men, the child penalty is smaller in magnitude across all specification, indicating that some of the child penalty in panel A is due to men who have children having slight increases in earnings post-birth. However, despite the difference in magnitude, there is still a larger child penalty for women living far from grandparents.

Table 4: Aggregated Child Penalty, by Distance to Grandparent

	Same County	Diff. County	Diff. County & > 25 mi.	Diff. State	Diff. State & > 25 mi.	1-25 mi.	26-50 mi.	> 50 mi.
Panel A: Male Control Group								
Mean Baseline	24219.6	26360.7	26015.7	27755.1	27506	30715.5	24737.1	26382.2
Post-Period	-13521.3***	-20510.3***	-20580.2***	-27375.3***	-27559.5***	-19682.0**	-10698.0***	-23428.6***
	(1684.7)	(1759.3)	(1843.9)	(2987.1)	(3012.7)	(5885.2)	(2919.3)	(2164.3)
Num. Households	727	1024	922	409	398	102	146	776
HH-Year Obs.	9014	11334	10120	4753	4624	1208	1800	8304
Panel B: Women Only, No Control Group	Same County	Diff. County	Diff. County & > 25 mi.	Diff. State	Diff. State & > 25 mi.	1-25 mi.	26-50 mi.	> 50 mi.
Mean Baseline	21299.3	21834.3	21419.6	21884.2	21751.9	26642.4	22609.3	21066.7
Post-Period	-7760.7***	-12134.2***	-11620.2***	-11415.4***	-11144.5***	-15029.7***	-12797.3***	-10940.3***
	(1215.1)	(1150.6)	(1195.7)	(1567.2)	(1558.1)	(2949.9)	(2131.1)	(1346)
Num. Households	723	1013	910	402	391	102	144	765
HH-Year Obs.	4911	6141	5477	2541	2471	648	933	4508

Note. This table reports the coefficients of a regression of earnings measures on indicators for years surrounding a woman's first birth, collapsed into the pre-period (3 to 5 years pre-birth),year prior to birth, year of the birth, and post-period (1 to 10 years post-birth). Two years prior to birth is omitted. Controls for year of survey, county fixed effects and age of mother are also included. Panel A is a specification which uses men as a control group; panel B only includes women. Distance is measured as the distance between the population centroid of the focal woman's county and the population centroid of the grandparent's county. Standard errors clustered at the individual level in parentheses.$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

We next do a similar exercise for those living in high or low childcare cost states. Using the US Department of Labor's National Database of Childcare Prices, we calculate the average weekly price for center-based toddler care by county and assign each county a percentile value indicating where in the distribution that county falls relative to the full distribution of county-level prices. The average respondent in our PSID sample lives in the 83rd percentile of the national distribution. We compare those who are living at or above the 75th percentile of the child price distribution ('High Cost') to women living below the 75th percentile ('Low Cost').

In Table 5, we report the aggregated post-birth effects of a child by childcare cost region for those above (column 1 and 4) and below (column 2 and 5) the 75th percentile in terms of childcare costs. We also run a specification that interacts the level of weekly childcare costs with the event study indicators (columns 3 and 6). Here, we see that a one-standard-deviation increase in childcare prices – \$48 per week – increases the child penalty by \$2,329, which is a 11% child penalty relative to the baseline earnings. Appendix Figure A.2 reports the coefficients for event study specification. The difference across childcare cost regions is of similar magnitude to the difference in the child penalty for those near vs. far from the child's grandmother but is not statistically significant until the age of two, consistent with the fact that children are less likely to receive out-of-home care in the first year of life.

Table 5: Aggregated Child Penalty, by Childcare Costs

	Male Control			No Control		
	> 75th Pct.	<75th Pct.	All	> 75th Pct.	< 75th Pct.	All
Baseline Mean	22837.4	16937.8	20393.3	28350.7	21385.6	25465.5
Post-Period	-12190.2***	-7411.1***	-1470.5	-19745.7***	-11170.8***	892.7
	(1057.1)	(947.6)	(1623.2)	(1607)	(1615.5)	(3443.5)
Post X CC Price (10s)			-485.3***			-970.5***
			(88.73)			(194.4)
Num. Households	1230	732	1692	1270	2269	1708
Num. HH-Year	7125	3971	10747	13137	7231	19706

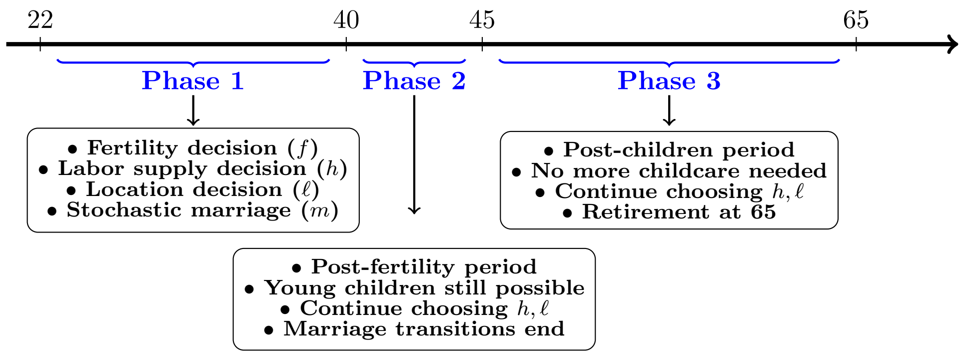
Note. This table reports the coefficients of a regression of earnings on indicators for years surrounding a woman's first birth, collapsed into the pre-period (3 to 5 years pre-birth), year of the birth, year prior to birth, and post-period (1 to 10 years post-birth). The year two years prior to birth is omitted. Col. 1-3 include men as a control group; Col. 4-6 do not. Controls for year of survey, age of mother, and county are also included. Columns 1 and 4 are for women living in counties with center-based childcare prices above the 75th percentile of the national distribution. Columns 2 and 5 are for women living in counties below the 75th percentile. Columns 3 and 6 are for the full sample and interact the event study indicators with the average weekly childcare price (unit= $10). Standard errors clustered at the individual level in parentheses.$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

3 Model

Taken together, these analyses demonstrate the importance of geographic proximity to affordable childcare for women's long-run labor market outcomes– whether it be informal care from a grandparent or less expensive private childcare. However, in both the analyses, we are not fully accounting for the joint selection process of location, fertility, and labor force participation. For example, when we observe that mothers living in high childcare cost regions earn less than those in low childcare cost regions, it may be that the mothers in low cost regions were motivated to select into those regions due to higher ability or attachment to the labor force that is known to them but unobserved to us as econometricians. Therefore, a model that places some assumptions on the selection process will be required to account for the endogeneity of migration decisions and to evaluate the impact of policy counterfactuals.

In particular, we are interested in how policies that may substitute for intergenerational time transfers (such as subsidized childcare) would influence the migration decisions and subsequent earnings of women who might otherwise rely on their parents to assist in child-rearing. Using our model, we will be able to explore the effectiveness of such policies in improving welfare for different types of parents, as well as decompose any effects on earnings into a direct effect of changes in attachment to the labor force due to childcare policies versus the secondary effects of the policies such as allowing households to sort into better paying labor markets.

Figure 3: Model Timing



Notes: Figure presents timing of phases of model and summarizes decisions made in each period. A period in the model is one year. See text for additional details.

Lastly, we estimate the model separately by race to explore heterogeneity in the value of these policies for Black mothers relative to White mothers. The frictions associated with childcare access may be particularly important in explaining racial gaps in migration rates and wages, as single motherhood is more common for Black mothers. Our descriptive analyses suggest that single mothers are more dependent on geographic proximity of family for access to care. Moreover, the descriptive analyses suggest that home migration at time of first pregnancy is more common for White and Black women, but not non-White/Black women. The model will allow us to precisely quantify the extent to which fertility events drive migration across demographic groups in the United States.

3.1 Setup and Timing of Decisions

Our model adapts the dynamic labor force participation of Eckstein and Wolpin [1989] and nests it in a simple framework of dynamic migration [Kennan and Walker, 2011] while incorporating multiple dimensions of family structure. The model is a dynamic discrete choice model that follows the fertility, labor force participation, and migration decisions of women.

Figure 3 presents a summary of the phases of the model and the decisions made in each period. A period is one year. Agents enter the model at age 22 and may choose to conceive each period until age 40. Between ages 40 to 45, though agents cannot get pregnant, they may either have young children or have no children. After age 40, we additionally assume

Table 6: Model Notation

Description		Values	Description		Values
Locations	ℓ	$\ell^P, \{1, ..., 9\}$	Years of Experience	x	[0,40]
Location Daycare Cost Types	δ	$\delta^\ell, \ell \in \{1, ..., 9\}$	Marital Status	m	0,1
Location Wage Effects	η	$\eta^\ell, \ell \in \{1, ..., 9\}$	Fertility Status	f	0,1
Location Costs of Living	κ	$\kappa^\ell, \ell \in \{1, ..., 9\}$	Spouse Wage FE	μ_S	μ_S^L, μ_S^H
College Attainment	e	0,1	Previous LFP Status	p	0,1
Age	a	[22,65]	Hours	h	0,1
Age of Youngest Child	a_c	$\emptyset$, [0,4]	Time Transfers; Spouse/Parents	τ	τ^S, $\tau^{P,m}$

Notes: Table presents model notation. Description of variables and symbolic representations are contained in the first two columns of each panel, while the potential values the variables can take are presented in the third column.

that the agent's current marital status remains fixed for the rest of the lifecycle. Agents choose whether to conceive, whether to supply labor and, afterward, whether and where to move until making a final labor force decision at age 65, after which they accrue no further utility. We select age 22 as the starting point to allow the bulk of higher education choices to be made while pre-empting the prime fertility years of U.S. women.

At the beginning of each period, the women in our model observe the location of their parents and stochastic realizations of their marital status. The women choose whether to conceive, which we model as entering a state wherein the woman knows with certainty she will have a child aged 0 in the subsequent period. Agents then choose whether to participate in the labor force, weighing increased utility from consumption should they choose to vs. preferences for leisure and savings on childcare expenditures should they not. Participation also increases future expected earnings through accumulating work experience. The women then choose where to live — in particular, their options include staying in their current location, moving to their parents' location, or moving anywhere else, which we collapse into the nine Census divisions.[6] Following their migration decision, women enter the subsequent period.

3.2 State Variables and Value Functions

Table 6 presents a complete summary of state variables and notation in the model, which are described in more detail in this section. Locations are indexed by ℓ, with ℓ^P denoting an agent's parent location. The other locations represent the nine Census divisions, each of which vary by childcare costs δ^ℓ, wage effects η^ℓ, and cost of living κ^ℓ. Static college

[6] See Appendix Table A.4 for division definitions. Agents are allowed to live in the same division as their parents while not being in the parent location, as well, so that they do not receive parental childcare time transfers. 72% of cross-state moves observed in the data involve cross-divisional moves.

attainment is indexed by $e \in \{0, 1\}$, endogenously determined years of experience by x, and deterministic age by a.

We now turn to describing notation for family structure.[7] Marital status is denoted by $m \in \{0, 1\}$ and is assumed to evolve entirely stochastically as a function of other state variables, described further in Section 4. Men make no decisions in our framework and inelastically provide monetary and childcare time transfers to their wives. The variable a_c captures the age of the youngest child in the household, provided that they are less than 5 years old.[8] The state $a_c = \emptyset$ stands for when the household has no children aged 5 or younger.

Meanwhile, the variable f captures the fertility status of the woman: if $f = 1$ in year t then $a_c = 0$ in year $t + 1$ with certainty. Having pregnancy be a known state allows our women to make migration and labor force participation decisions *in anticipation* of fertility events. Women are allowed to have multiple children in that their f state may equal 1 even if the household currently contains a young child, in which case a_c will be reset to zero in the subsequent period. We shut down fertility events at age 40, meaning that when women leave the model at age 45 all children have aged out of early childhood.

Women are endowed with a single unit of time each period and may choose to work full time ($h = 1$) or not at all ($h = 0$). Subsuming all the state variables outside of the agent's fertility status and current location into the vector Ω, the agent begins the period by choosing whether or not to conceive:

$$\begin{aligned} V^1(\Omega, \ell) \quad &= \quad \max_{f \in \{0,1\}} \left\{ \mathbb{E}_{\varepsilon_w}[V^2(\Omega, \ell; f)] + f \cdot (\theta_1 + \theta_2 a + \theta_3 m + \theta_4 am + \theta_5 e + \varepsilon_f) \right\}, \\ & \qquad \varepsilon_f \sim N(0, \sigma_f), i.i.d. \end{aligned} \tag{2}$$

If the agent is older than 40, conception is no longer an option, and we have $V_1(\Omega, \ell) = \mathbb{E}_{\varepsilon_w}[V_2(\Omega, \ell; 0)]$ and assume that $\varepsilon_f = 0$. Conceiving involves utility costs that include a fixed component along with variable costs that depend on the agent's age, marital status, an age-marital-status interaction, and an education effect. To allow for individual heterogeneity in fertility decisions, we also include a random component ε_f – thus, the agents in the model

[7] We omit individual and time subscripts in this section for readability.

[8] We currently do not keep track of the number of young children and instead focus on the presence of any at all. Rosenzweig and Wolpin [1980] study the effects of twins on labor force participation and find that women with twins exhibit a labor force participation rate 0.371 pp lower than women without. While these effects are meaningful, we view their magnitude as small enough to permit the omission to ease computation. This almost certainly means that we are understating the costs of childcare and the potential effects of subsidies to them in terms of labor force participation and wages.

will only choose to conceive if their draw of ε_f is above a certain threshold.

The agent also considers how happy they expect to be when they move to the labor supply phase of the period, given by V_2. We first discuss the labor supply decision in the case of a woman with no young children to attend to:

$$\begin{aligned} V^2(\Omega, \ell; f) &= \max_{h \in \{0,1\}} \Big\{ \alpha_1(c) + (1-h)(\alpha_2 + \alpha_e e + \alpha_x + \alpha_c c) + \alpha_3 \mathbb{1}(h \neq p) \\ &\quad + \alpha_4 \mathbb{1}(\ell = \ell^P) + \boldsymbol{\alpha_\Gamma \Gamma} + \mathbb{E}_{\zeta_{\ell'}}[V^3(\Omega, \ell; f, h)] \Big\}; \qquad (3) \\ \kappa^\ell c &= w_S \mathbb{1}(m=1) + wh. \end{aligned}$$

Thus, α_1 rescales utility over consumption in dollars to util terms[9], and α_2 represents a preference for leisure. Preferences for leisure are further modified based on experience (α_x) or if the agent has a college degree (α_e), and α_c represents a consumption-leisure complementarity that makes married women less likely to work. The parameter α_3 constitutes a penalty borne from changing one's labor force participation status, allowing the model to account for frictions individuals face in moving in and out of the labor force. The utility premium for currently being in one's parent's location is captured by α_4. Locations differ in amenities $\boldsymbol{\Gamma}$ that include average distance to shore taken from Lee and Lin [2017], average number of warm-weather days in a calendar year taken from Kennan and Walker [2011], and an index of other amenities related to government provisions and quality of life taken from Diamond [2016] which have been identified as salient drivers of location decisions. While we do not explicitly model decisions over housing or consumption of other location-specific, non-childcare products to impact utility, we allow the price of consumption κ^ℓ to differ by location, allowing for differences across Census divisions in costs for goods like housing, transportation, food, etc. to influence location choice.

Consumption here is given by the wages of the woman's spouse (assumed to be supplied inelastically and equal to zero if the woman is unmarried) and the earnings of the woman herself. Log wages of the woman and her spouse are given by the following equations:

$$\log(w) = \beta_0 + \boldsymbol{\beta X} + \eta^\ell + \varepsilon_w + \xi; \qquad \log(w_S) = \beta_{S,0} + \boldsymbol{\beta}_S \boldsymbol{X}_S + \mu_S + \eta^\ell;$$

$$\varepsilon_w \sim N(0, \sigma_w) \text{ i.i.d}; \quad \xi \sim N(0, \sigma_\xi) \text{ i.i.d.}$$

[9]We scale consumption so that one unit of consumption corresponds to \$2,080. This can be thought of as one hourly wage unit, since working 40 hours per week, 52 weeks pear year would imply that an additional dollar increase in hourly wages would increase one's annual budget by \$2,080.

The vector of observables of the spouse $\boldsymbol{X}_S$ contain a college dummy and a quadratic in experience. We also include a high-earning and low-earning spouse type, $\mu_S \in \{\mu_S^L, \mu_S^H\}$. The agent's observables $\boldsymbol{X}$ contain the same standard Mincerian combination along with dummies for having a child aged 0-1 or a child aged 2-4.[10] With the assumption that husbands supply labor inelastically, the terms of the husband's wage equations can be uncovered directly from data if we assume husbands to be identical to their wives in age and schooling level, and husband earnings types can be inferred from the individual fixed effects we estimate for them. While assortative mating by education is not perfect in practice, the spouse wage types allow for lower-educated women to have higher-earning spouses, and vice-versa. We estimate the components of the woman's wage process within the model. Location fixed effects, η are also assumed to be constant across time and equal for men and women, which with the assumption of exogenous male labor supply will allow us to estimate values for η outside the model using male wages. Wages for women include a transient component ε_w that will be the key factor in determining whether a woman works and are measured with error ξ assumed uncorrelated with ε.

The final term of Equation (3), $\mathbb{E}_{\zeta_{\ell'}}[V^3(\Omega, \ell; f, h)]$, represents the expected continuation value given the woman's labor force participation decision. Following her choice of h, the woman receives a series of location preference shocks that will determine her location choice:

$$V^3(\Omega, \ell; f, h) = \max_{\ell'} \left\{ \beta \sum_{\Omega'} \mathbb{E}_{\varepsilon_f}[V^1(\Omega', \ell')] \mathbf{Pr}(\Omega' | \Omega, f, h, \ell') - \Delta(\Omega, \ell') \mathbb{1}\{\ell' \neq \ell\} + \zeta_{\ell'} \right\}. \tag{4}$$

The agent takes into account possible state transitions Ω' and expected next-period utility after solving her optimal labor supply problem and optimizes her choice of next-period location following a series of location preference shocks $\zeta_{\ell'}$ distributed Type 1 EV with location 0 and the scale parameter normalized to 1. Allowing for such shocks to influence migration decisions is critical, given that moves for apparently non-pecuniary reasons are a salient feature of the data [Kennan and Walker, 2011]. Marriage transitions are governed by stochastic functions that we calibrate directly from the data. We assume that the woman can no longer become pregnant at age 40 and that their marriage state at age 40 carries on for the remainder of the life cycle. The agent's next value of p (past-period labor force participation) depends on her selection of h. The agent's experience x increments by 1 should she choose to work and 0 if she does not, and the agent's age a increments by 1 with

[10]While we abstract away from an explicit part-time choice, this allows the model to be consistent with mothers of young children preferring more flexible/ lower-paying jobs.

certainty. Next-period utility is discounted by the factor β.

The parameter $\Delta(\Omega, \ell')$ captures moving costs that the agent faces should they have chosen to do so, which itself depends on other elements of the state space. If a woman moves across locations in a period, she must incur moving costs given by

$$\Delta(\Omega, \ell') = \gamma_0 + \gamma_1 e + \gamma_2 \mathbb{1}\{a_c \neq \emptyset\} + \gamma_3 m + \gamma_4 N^{\ell'} + \gamma_5 a. \tag{5}$$

Moving costs involve a fixed cost and costs that vary with college education, marriage, age, and presence of young children. While the purely monetary costs of moving are relatively small, the non-pecuniary burdens of moving may be large, and these terms capture these costs while allowing them to vary along demographic lines. Furthermore, we allow for moves to larger locations (N^ℓ represents the population of division ℓ in tens of millions) to be less costly as in Kennan and Walker [2011], representing that more populous locations may be more likely to contain social contacts for movers or easier-to-navigate job markets.

Finally, a woman with young children in the working stage of the model enjoys utility:

$$\begin{aligned} V^2(\Omega, \ell; f) &= \max_h \Big\{ \alpha_5(c) + (1-h)(\alpha_6 + \alpha_e e + \alpha_x x + \alpha_c c) + \alpha_3 \mathbb{1}(h \neq p) \\ &\quad + \alpha_7 \mathbb{1}(\ell = \ell^P) + \boldsymbol{\alpha}_{\boldsymbol{\Gamma}} \boldsymbol{\Gamma} + \mathbb{E}_{\zeta_{\ell'}}[V^3(\Omega, \ell; f, h)] \Big\}; \qquad (6) \\ \kappa^\ell c &= w_S \mathbb{1}(m=1) + wh - \delta^\ell \cdot \max\Big\{0, h - \tau^S \mathbb{1}(m=1) - \tau^{P,m} \mathbb{1}(\ell = \ell^P)\Big\}. \end{aligned}$$

The specification thus flexibly allows women with young children to have different preferences for consumption, leisure, and location. When young children are present, the agent must also either dedicate time to caring for their children or absorb childcare costs, which depend on their current location, the current location's type, and the woman's marital status. Women never pay for childcare costs if they do not work ($h = 0$), and spouses and grandparents contribute fixed time transfers to childcare (τ^S and $\tau^{P,m}$) if the woman is either married or living in her parent's location. The grandparents' contribution varies based on the marital status of the woman — this, along with women differing in their budget constraint and moving costs along marital status, allows the model to potentially capture differential behavioral patterns among married and unmarried women, as was suggested by the empirical analysis. Differences in labor supply for married and unmarried women outside of the grandparent location will be useful for identification of τ^S, while labor supply patterns of women within marital types located in and out of the grandparent location will be informative for $\tau^{P,m}$.

Furthermore, we allow for unobserved heterogeneity in grandparent helpfulness, such that with probability P_τ the agent's parents will provide time transfers of zero.

3.3 Model Solution

The model is solved via backward induction. If the agent is in the phase of the model where fertility is possible, her fertility decisions will be governed by whether her fertility utility shocks ε_f are sufficiently high. Afterward, labor force participation is governed by whether the transient component of the wage offer ε_w is sufficiently high. We compute cutoff values of ε_w for each element in the state space, after which continuation values can be computed by applying the usual type-1 extreme value formula and using the cutoff values in conjunction with properties of the normal distribution to solve for an agent's expected flow utility in the next period. A more detailed description of the procedure and the algebraic details for solving cut-off values is described in Appendix B.1.

4 Estimation

4.1 Data

We use data on non-Hispanic White and Black women aged 22-40 in the 2001-2019 waves of the PSID.[11] All women must be observed at least through ages 22 to 25 to be included in our sample. The PSID shifted to a biennial schedule starting in 1997 — however, in years following 2000, respondents were asked their income and hours worked for both the preceding year and the year before. Furthermore, if the respondent had moved across states since their most recent interview, they were asked in which year the move was made. This information, combined with marital and childbirth histories for all respondents, allows us to construct yearly data from the biennial survey with minimal assumptions. Importantly, the PSID additionally allows for intergenerational linkages, through which we can track the location of the parents of the respondent. For additional details on the sample construction, refer to Online Appendix B.2.

Our sample construction leaves us with a sample of 932 women and 10,122 person-year observations. The median woman in our sample is observed for seven years (i.e., up through age 28), and Appendix Table A.5 for a complete tabulation of ages in our analysis sample.

[11]Sample size limitations prevent us from looking at additional demographic subgroups.

Appendix Table A.6a presents descriptive demographic and economic statistics broken down by age ranges and race, while Appendix Table A.6b presents migration statistics in our estimation sample with additional breakdowns by race.[12] White women in the sample are considerably more mobile than their Black counterparts, even when conditioning on factors such as the presence of young children and marital status. However, among movers, the share who move back to the parent location across race is roughly constant across race.

4.2 Parameters Estimated Outside the Model

We assume a discount rate of $\beta = 0.95$. Childcare costs levels δ for an hour of care are at the division level using previously described data from the NDCP. We average center-based prices across age groups and collapse to the division level weighted by the number of households with children under six per county, keeping data before 2016 to be consistent with our estimation sample. Costs of living κ^{ℓ} are taken from the American Chamber of Commerce Research Association's Cost of Living Index.[13] The parameters governing spousal wages are taken from a comparable PSID sample to our analysis sample. With the assumption that husbands supply labor exogenously and are of the same age and education level as their wives, these parameters can be estimated directly from Mincerian wage regressions. Since we assume location wage effects to be equal between men and women, this also allows for the recovery of location wage effects η^{ℓ}, which are again grouped at the division level. Division populations N^{ℓ} come from year-2000 Census population estimates.

Figure A.1 in the online appendix gives a graphical representation of division-level childcare costs, wage effects, and living costs.[14] Unsurprisingly, these measures are highly correlated across locations, with high-wage divisions also usually having high costs of living and high childcare costs. However, the relationships are not exact, with the correlation of wage effects and childcare prices (both being adjusted for living costs) being approximately 0.75.

[12]We do not use sample weights when creating these statistics or when estimating our model. Including longitudinal sample weights available in the PSID does little to change our parameter estimates.

[13]The ACCRA index is a weighted average of costs of food, housing utilities, transportation, health care, and miscellaneous goods and services among different metro areas in the United States. State-level indices have been published from 2016 onward by the ACCRA, and a state-level index constructed by Kennan and Walker [2011] for around 1980 is also available. Given high correlation of local cost-of-living across years ($\rho = 0.8$), we take the midpoint of the 1980 and 2016 indices while normalizing the cost-of-living level of Iowa to be zero before averaging by division with population weights.

[14]When estimating the model separately by race, we also estimate race-specific values of η^{ℓ} and β_S. We also raise childcare costs for married, college-educated women by a quantity consistent with Berlinski et al. [2023] to reflect this group on average selecting higher-quality and more expensive options, though the childcare quality choice is not explicitly modeled here.

Table 7: Parameters Estimated Outside the Model

Parameter		Value
Discount rate	β	0.95
Childcare cost levels	δ^{ℓ}	Various
Location wage effects	η^{ℓ}	Various
Location living costs	κ^{ℓ}	Various
Location populations	N^{ℓ}	Various
Spouse wage, constant	$\beta_{S,0}$	2.234
Spouse wage, education	$\beta_{S,1}$	0.571
Spouse wage, experience (linear)	$\beta_{S,2}$	0.047
Spouse wage, experience (quadratic)	$\beta_{S,3}$	-0.0007
Spouse wage, fixed effects	μ_S^L, μ_S^H	-0.39, 0.39

Notes: Table reports values of parameters that are estimated outside the model. Columns 1 and 2 describe the parameters and present their symbolic representation. Column 3 reports parameter values. See text for details on model and sample construction. See Figure A.1 for representations of state-level childcare costs, wage effects, and living costs.

This will result in contrasting migration incentives for women with and without children, and the extent to which we observe these types of women behave differently in the data will be crucial in identifying preferences for consumption and will prevent us from mechanically overstating the role of childcare costs in influencing labor mobility.

We estimate marital transitions via linear probability models using our estimation sample that admit as inputs whether the agent is currently married, a parent to young children, and a cubic polynomial in age. Probabilities of marital dissolution and formation vary over spousal wage type μ_S. We calculate all probabilities separately for women with and without a college degree as well as by race. Appendix Figure A.3 presents the fit of our model with regards to life-cycle profiles of marriage rates and indicates that our model fits the data well.

4.3 Estimation and Identification

We use maximum likelihood to estimate the remaining parameters of our model using the Sbplx algorithm.[15] The joint likelihood function for labor force participation, wages, and

[15] A variation on the Subplex algorithm, which itself applies the Nelder-Mead method on a sequence of subspaces; see https://nlopt.readthedocs.io/en/latest/NLopt_Algorithms/.

migration for the N women in our sample, each observed for T_i periods, is given by:

$$L = \prod_{i}^{N} \sum_{\tau} \mathbf{Pr}(\tau) \prod_{t=1}^{T_i} \mathbf{Pr}(f = f_{it}|\Omega_{it}, \ell_{it}) \cdot \mathbf{Pr}(h = h_{it}|\Omega_{it}, \ell_{it}, f_{it}) \cdot$$
$$\mathbf{Pr}(w = w_{it}|\Omega_{it}, \ell_{it}, f_{it}, h_{it}) \cdot \mathbf{Pr}(l' = l'_{it}|\Omega_{it}, \ell_{it}, f_{it}, h_{it}).$$

Further details on the functional form of the probabilities are given in Appendix Section B.3.

We employ a mixture model over unobserved heterogeneity in grandparent transfers, letting $\mathbf{Pr}(\tau)$ denote the probability of the agent being unobserved type τ. We assign the educational state based on whether women in our sample *eventually* obtain a college degree, but since in practice some individuals who obtain a college degree do so in their mid-20s, we exclude observations age less than 25 with a college degree when evaluating the likelihood. The relationship between labor force participation and migration decisions in our model are identified from jointly observing participation, earnings, and location choices for women, conditional on demographic characteristics and location of grandparents.

First, we assume that the shocks drawn in the model – location preferences, earnings shocks, fertility realization, marriage realization – are all independently and identically distributed across individuals and time. While this may seem a strong assumption at first, we do allow the likelihood of pregnancy and marriage to vary on observable characteristics, including many of the factors that contribute to a woman having a higher or lower earnings potential. This means that this assumption relies only on the weaker assumption that preferences for pregnancies and marriages are not correlated across time with the transitory component of earnings that varies idiosyncratically across time. Due to high rates of unintended and mistimed births in the US, we believe this is a reasonable assumption. The assumption of independence of location preference shocks and earnings shocks is a stronger assumption: we assume that wage differences across time/individuals are not place-specific and not correlated with amenities in a location in a given year. While the inclusion of amenities along with a reasonably rich wage process in the model helps justify this assumption, allowing for additional heterogeneity in idiosyncratic wage match effects may be helpful as well.

With these distributional assumptions in place, identification of the structural parameters falls out cleanly from the maximum likelihood estimation equation. Following Eckstein and Wolpin [1989] and using equations for reservation wages in Appendix B.1, the reservation wages ε^*, the wage parameters ($\beta_0, \boldsymbol{\beta}$, and μ), and σ_w and σ_ξ are all identified from data on participation and wages. We can then use the identified ε_w^* and our equation for the definition of the reservation wage described in Appendix B.1 to identify $\frac{\alpha_2}{\alpha_1}, \frac{\alpha_e}{\alpha_1}, \frac{\alpha_\mu}{\alpha_1}, \frac{\alpha_c}{\alpha_1}$, and $\frac{\alpha_3}{\alpha_1}$. Based on the similar equation for women with young children, we can identify $\frac{\alpha_6}{\alpha_5}, \frac{\alpha_e}{\alpha_5}, \frac{\alpha_\mu}{\alpha_5}, \frac{\alpha_c}{\alpha_5}, \frac{\alpha_3}{\alpha_5}, \tau_{p1}, \tau_{p0}$, and τ_s. Using any combination of pairs in which the leisure parameter is the same across the presence of children (e.g., $\frac{\alpha_e}{\alpha_1}, \frac{\alpha_\mu}{\alpha_1}, \frac{\alpha_e}{\alpha_5}, \frac{\alpha_\mu}{\alpha_5}$) would allow us to separately identify α_1 and α_5 and thus separately identify all α parameters governing leisure. Similar arguments allow us to identify the θ parameters that govern fertility decisions in the model.

The remaining parameters include the parameters governing preferences for the parent's location, amenities, and the moving cost parameters. We can identify the parent's location preference parameter off the difference in the likelihood of moving to the parent's location ℓ^p from some location k and the likelihood of moving to a non-parent's location from that same location k for agents who are similar on all demographic characteristics. The same logic applies for identifying the amenity utility parameters $\boldsymbol{\alpha}_{\boldsymbol{\Gamma}}$. The moving cost parameters are identified off the differences in likelihood of moving from location j to k versus staying in location j by demographic group. The parameter on population is identified off of the relative likelihood of moving from a small division to a large division vs. from a large division to a small division.

5 Results

Table 8 reports the parameter estimates. Standard errors are computed via inverting the numerical Hessian of the likelihood function and taking its diagonal.

The estimation recovers preferences for consumption and leisure that increase and decrease respectively over the presence of a small child. The disutility associated with changing one's labor force participation status is substantial, and we find higher leisure preferences for women with high earnings potential, which rationalize their rates of labor force participation that, while higher than low-earning women, are still lower than those of men. The leisure-consumption complementary α_c is positive, reflecting women being less likely to work with higher-earning spouses, all else held equal. The estimates of wage returns to a college degree and experience are all in line with previous estimates in the literature. We also estimate a meaningful reduction in wages associated with having a child between 0 and 1 year old, but the effect of older children on wages is statistically insignificant.

The estimates of time transfers τ suggest that informal care considerably offsets the direct cost of childcare for women with children — indeed, helpful grandparents cover more

Table 8: Parameters Estimated via Maximum Likelihood

Parameter		$\hat{\theta}$	$\hat{\sigma}_\theta$	$\hat{\theta}$	$\hat{\sigma}_\theta$	$\hat{\theta}$	$\hat{\sigma}_\theta$
Fertility							
Fixed cost	θ_1	1.006	0.355	1.325	1.180	0.924	0.280
Age effect	θ_2	0.098	0.002	0.101	0.035	0.097	0.025
Marriage effect	θ_3	3.655	0.252	4.108	1.431	3.713	0.401
Age-marriage interaction	θ_4	0.107	0.008	0.107	0.045	0.120	0.019
Education effect	θ_5	0.311	0.121	0.432	0.155	0.183	0.240
Fertility shock SD	σ_f	2.681	0.314	2.703	0.395	2.708	0.473
Utility							
Consumption, no children	α_1	0.084	0.005	0.084	0.015	0.088	0.033
Leisure, no children	α_2	1.001	0.055	0.999	0.188	0.987	0.403
LFP switch penalty	α_3	-0.097	0.003	-0.115	0.018	-0.076	0.03
Parent preference, no children	α_4	0.158	0.015	0.163	0.014	0.124	0.029
Consumption, with children	α_5	0.092	0.006	0.090	0.016	0.093	0.036
Leisure, with children	α_6	0.865	0.046	0.869	0.157	0.855	0.367
Parent preference, with children	α_7	0.167	0.030	0.143	0.037	0.182	0.052
Consumption/leisure complementarity	α_c	0.003	0.000	0.003	0.000	0.000	0.001
College leisure preference modifier	α_e	0.493	0.019	0.503	0.092	0.488	0.203
Experience leisure preference modifier	α_x	0.000	0.001	0.000	0.002	0.000	0.003
Amenity preference: distance to shore	$\alpha_{\Gamma,1}$	-0.001	0.003	0.000	0.004	-0.008	0.009
Amenity preference: amenity index	$\alpha_{\Gamma,2}$	0.022	0.019	0.019	0.024	0.078	0.033
Amenity preference: warm days	$\alpha_{\Gamma,3}$	0.008	0.018	-0.042	0.023	0.135	0.034
Time Transfers							
Spouse time transfer	τ^S	0.079	0.043	0.055	0.062	0.047	0.105
Parent time transfer, unmarried	$\tau^{P,0}$	0.528	0.031	0.545	0.065	0.686	0.046
Parent time transfer, married	$\tau^{P,1}$	0.494	0.040	0.512	0.049	0.524	0.104
Probability of $\tau^P = 0$	P_τ	0.588	0.036	0.679	0.045	0.511	0.052
Wages							
Wage intercept	β_0	1.943	0.014	1.944	0.019	1.930	0.037
College effect	β_1	0.493	0.012	0.489	0.016	0.501	0.022
Experience effect, linear	β_2	0.075	0.001	0.075	0.002	0.075	0.004
Experience effect, quadratic	β_3	-0.002	0.000	-0.002	0.000	-0.002	0.000
Child aged 0-1	β_4	-0.063	0.013	-0.047	0.017	-0.075	0.021
Child aged 2-4	β_5	–0.011	0.013	0.009	0.018	-0.026	0.021
Wage shock SD	σ_ε	0.231	0.008	0.247	0.010	0.249	0.011
Wage measurement error	σ_ξ	0.364	0.005	0.365	0.006	0.343	0.008
Moving Costs							
Fixed cost	γ_0	4.599	0.220	4.598	0.264	4.591	0.405
College effect	γ_1	0.299	0.113	0.249	0.129	0.233	0.221
Child effect	γ_2	0.065	0.121	0.034	0.144	0.177	0.214
Marriage effect	γ_3	0.394	0.120	0.473	0.147	0.192	0.265
Population effect	γ_4	-0.159	0.053	-0.196	0.063	-0.186	0.095
Age effect	γ_5	0.028	0.012	0.023	0.005	0.048	0.031
Sample		All		Whites		Blacks	
N		10,122		6,108		4,014	
Individuals		932		549		383	
Log Likelihood		-11,894		–7,057		-4,848	

Notes: Table presents estimates and standard errors of parameters estimated via maximum likelihood. Data from PSID. See text for details on sample construction and formation of likelihood function.

than half of childcare expenditures. Moreover, we estimate statistically and substantively significant differences in informal care usage by race: unmarried Black women receive a childcare reduction of nearly 70% from their helpful grandparents, and Black women are approximately 20 p.p. more likely to have informal care available.

We estimate positive preferences for residing in the parent location, suggesting that agents place a premium in being in their parent's location even after accounting for informal childcare transfers. We also estimate a version of the model without these transfers to quantify how important the informal childcare channel is in informing home preferences. Without childcare transfers, we estimate parent location preference parameters of 0.165 and 0.180 for women without and with children, suggesting that grandparent informal care can explain 5 to 10% of the home preference among U.S. women. Amenity preference estimates indicate that the agents in our model prefer higher levels of the Diamond [2016] amenity index, shorter distances to shores, and warmer weather, but only the last of these factors is estimated to be statistically significant. The moving cost estimates suggest that moving is less expensive (in terms of utility) for college graduates, but more expensive for married and older women. Moreover, moving to larger populations is meaningfully cheaper in terms of utility.

Because utility is linear in consumption, we are able to convert the moving parameters into dollars by dividing by the consumption scaling parameter and then multiplying by the consumption equivalence unit. For the "average" mover, the moving cost is about \$104,867, ignoring the value of the payoff shocks.[16] For comparison, a woman's lifetime earnings gain would be \$97,000 if, holding all other behavior constant, she moved from the lowest paid region to the highest paid region at age 22 and then stayed in that region for the remainder of her life. Though this is the most extreme example of the potential earnings gains from a move, it demonstrates that our moving costs net of payoff shocks are of a comparable magnitude to the potential earnings gains. However, we will note that these moving costs are the estimated costs for a hypothetical move to an arbitrary location, whereas in the model people will only choose to move to high pay-off locations. Thus, these average costs are higher than the costs that households which actually choose to move will face once pay-off shocks are accounted for.[17]

[16] To calculate, we sum Δ for all individuals who move, discounted by the relevant consumption scaling. That is $\bar{\Delta} = 2080 \times \frac{1}{N_{move}} \sum_{i=1}^{N_{move}} \left[\left(\frac{\mathbb{1}(a_c \neq \emptyset)_i}{\alpha_5} + \frac{\mathbb{1}(a_c = \emptyset)_i}{\alpha_1} \right) \times (\gamma_0 + \gamma_1 e_i + \gamma_2 \mathbb{1}(a_c \neq \emptyset)_i + \gamma_3 m_i + \gamma_4 N_i^{\ell'} + \gamma_5 a) \right]$.

[17] See Kennan and Walker [2011] for further discussion of the distinction between average moving costs versus average moving costs conditional on moving. Kennan and Walker [2011] show that while the moving costs for households that choose to move to their home location are large, moving costs to non-home locations

We also estimate racial heterogeneity in moving costs: we see that Black women have higher moving cost reductions than White women from having children but lower moving cost reductions from being married. The estimates of fertility parameters suggest that being married makes having children more likely, as does being younger, but the extent of racial heterogeneity across these parameters is limited. The spread of fertility preference shocks is also quite large, suggesting that fertility responses to counterfactual policies will be limited in nature.

5.1 Goodness of Fit

To assess our model's ability in approximating the true data generating process, we randomly simulate the outcomes of each woman in our estimation sample ten times, starting at age 22 and ending at the final age the given woman is observed in the data, using Bayes' rule to draw unobserved types. We then compare key moments in the estimation sample to those in our simulated data. We use our separate parameter estimates for White and Black women when simulating data for all model fit and counterfactual evaluations.

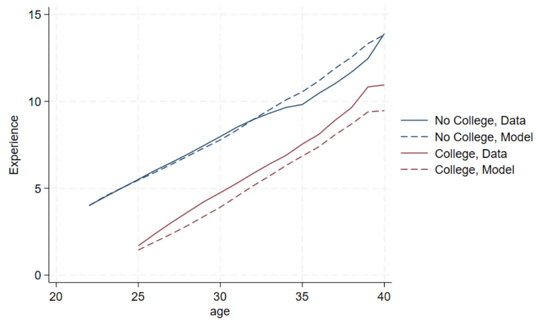
Figure 4 presents our model's fit of lifecycle profiles of labor market outcomes separately for women with and without a college degree. The model fits the data well, reproducing profiles of wages and experience accumulation that look very similar to the data. The model slightly understates labor force participation and earnings for women with a college degree at the beginning of the lifecycle, but the fit for non-college-educated women is nearly exact.

We evaluate the model's fit of labor force participation in more detail in Table 9 by breaking up labor force participation by fertility status, marital status, and proximity to parents. Qualitatively, the model can reproduce patterns of lower participation rates for mothers of young children and unmarried women. Across all women, the profile of labor force participation the model outputs over different locations and fertility statuses is reasonable. However, the model does understate participation for pregnant women as a whole.

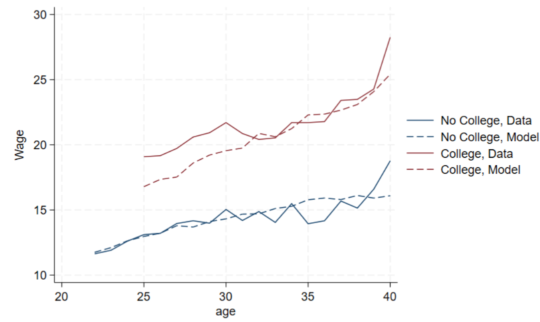
Next, we assess the model's fit of migration decisions by breaking down moves according to sending location, destination, and fertility status in Table 10. Since the PSID can have very small samples of movers and migration rates have wide confidence intervals, we supplement the table with statistics from the ACS sample used in Section 2 as well. Among all women and women without children, the model predicts rates of migration both out and into the parent location that are similar to those observed in the data, especially the ACS. Moreover,

are actually negative, representing the fact that these moves are ones with large expected future payoffs for the households who make them.

Figure 4: Model Fit: Labor Force Lifecycle Profiles



(a) Experience



(b) Hourly Wage

Notes: Data from PSID. Figures compare life-cycle trends of experience and wages for women with and without a college degree in estimation sample and data simulated from model. Fit reported for all ages for women with a high school degree and ages 25-onward for women with a college degree. See text for details on sample construction.

the model is able to match the pattern observed in the ACS of pregnant women moving back to their parents' location more frequently, while such behavior is not observed for women with young children in general. We also evaluate the model's fit of fertility profiles in Figure 5. The model's fit of lifecycle fertility profiles by both race and education is excellent.

An analysis of the frequency of repeat movers in our simulation also allows us to speak to the importance of allowing for dynamics when modeling migration decisions. While the probability of a move in any given year is small, the proportion of individuals who move at least twice in our estimation sample is non-trivial (8.26 percent in the data vs. 11.52 percent in the simulation). Moreover, this measure is severely understated due to our often ceasing to observe agents directly in our estimation sample by their late 20s. When we simulate all individuals through the entire life cycle, we observe that over 25% have moved multiple times by age 45. This indicates that agents will indeed re-optimize location decisions if allowed to do so, and a dynamic model is clearly needed to capture this richness of behavior.

Finally, we evaluate the frequency of grandparent childcare usage observed in our simulated data and compare it to external statistics. Specifically, we compare our informal care usage rates to the share of parents who use relative care as their main form of childcare the 2001 Early Childhood Longitudinal Study, as reported by Berlinski et al. [2023]. The authors report that 18 and 23 percent of married and single parents, respectively, use relatives as their main source of childcare. We measure informal care usage in our simulated data

Table 9: Model Fit: LFP by Location, Marital Status, and Fertility

Panel A: Data

	Overall			In Parent Location			Not In Parent Location		
Marital Status	No Kids	Pregnant	Kids	No Kids	Pregnant	Kids	No Kids	Pregnant	Kids
All	0.627	0.681	0.406	0.617	0.676	0.422	0.663	0.696	0.339
$m = 0$	0.647	0.655	0.453	0.630	0.635	0.458	0.711	0.773	0.416
$m = 1$	0.593	0.696	0.372	0.594	0.707	0.391	0.588	0.671	0.314
Observations	5140	385	4597	4017	293	3726	1123	92	871

Panel B: Model

	Overall			In Parent Location			Not In Parent Location		
Marital Status	No Kids	Pregnant	Kids	No Kids	Pregnant	Kids	No Kids	Pregnant	Kids
All	0.621	0.500	0.396	0.620	0.511	0.430	0.624	0.461	0.249
$m = 0$	0.658	0.567	0.457	0.654	0.570	0.481	0.675	0.549	0.314
$m = 1$	0.566	0.455	0.350	0.568	0.466	0.388	0.561	0.419	0.218
Observations	51679	4762	44779	40585	3757	36393	11094	1005	8386

Notes: Data from PSID. Table compares labor force participation rates for women in estimation sample and data simulated from model. Pregnancy corresponds to woman being pregnant with their first child. See text for details on sample construction.

Table 10: Model Fit: Migration by Fertility

Panel A: Data

Direction	All	No Kids	Pregnant	Kids
ℓ^p Out-Migration Rate	1.88	2.28	2.72	1.43
ℓ^p In-Migration Rate	4.77	4.58	6.58	4.82

Panel B: Out of Sample (ACS)

Direction	All	No Kids	Pregnant	Kids
ℓ^p Out-Migration Rate	1.80	2.03	1.64	1.31
ℓ^p In-Migration Rate	4.04	4.15	4.52	3.45

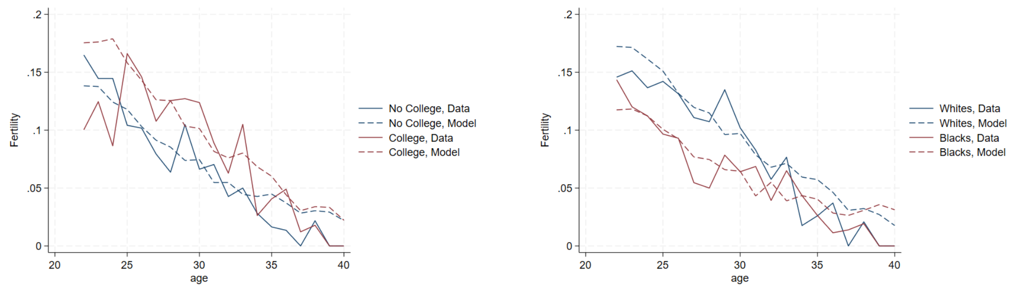
Panel C: Model

Direction	All	No Kids	Pregnant	Kids
ℓ^p Out-Migration Rate	1.89	2.07	2.13	1.67
ℓ^p In-Migration Rate	3.48	3.24	4.58	3.67

Notes: Data from PSID and ACS. Table compares migration rates for women in estimation sample and data simulated from model. Pregnant corresponds to being pregnant with one's first child. See text for details on sample construction.

as the share of women with young children who 1) live in the same location as their own parents, 2) are of the "helpful" grandparent type, and 3) choose to supply labor. Using this metric, we estimate informal care usage rates for married and single women of 18 and 28 percent, respectively, which compares well to Berlinski et al. [2023], particularly given that our measure doesn't explicitly observe grandparent informal childcare and that our PSID sample over represents low-income individuals who are more likely to rely on informal care

Figure 5: Model Fit — Fertility Life-Cycle Profiles



(a) By Education

(b) By Race

Notes: Figure presents model fit of fertility rates over lifecycle for women in PSID analysis sample and in data simulated from model. See text for details on sample construction.

in general. We also note that our sample uses later birth cohorts of children than Berlinski et al. [2023], and as formal childcare prices have increased over time, so too has informal care usage likely become more frequent.

6 Counterfactual Analysis

Having evaluated our model's performance, we now turn to comparative statics exercises.

6.1 The Role of Grandparents

We begin by evaluating the role of grandparents in wage formation, fertility, and migration by removing them entirely by setting grandparent time transfers $\tau^{P,m}$ to zero. Conceptually, the impact of the presence of grandparents on wages is ambiguous, since residing with them may increase labor supply and experience in the short run but may also impact wages negatively by discouraging moving to higher-paying locations.

Table 11 presents the results of this exercise. For this counterfactual as well as for those upcoming, we estimate impacts in terms of average effects on lifetime real wages, years of experience, fertility, and several migration measures. In particular, we measure the number of moves women make all together as well as moves made to the home location, away from the home location, and moves made between two non-home locations. We also calculate a willingness-to-pay metric by taking the difference in ex-ante utility (that is, utility at the

Table 11: Effects of Removing Informal Care from the Model

Sample	Wages	Years x	# Moves	Home Moves	Away Moves	Oth. Moves	Fert. f	WTP	WTP, $\gamma_1 = \infty$
All	-25.54	-0.70	0.03	0.00	0.01	0.02	-0.07	-3.21	-3.51
$\tau^P \neq 0$	-64.28	-1.77	0.07	0.00	0.01	0.05	-0.19	-8.07	-8.85
$\tau^P = 0$	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Never SM	-27.55	-0.70	0.02	0.00	0.00	0.02	-0.04	-2.49	-2.65
Ever SM	-23.86	-0.71	0.03	0.00	0.01	0.02	-0.10	-3.80	-4.22
Whites	-32.24	-0.80	0.02	0.00	0.00	0.02	-0.05	-2.47	-2.65
Blacks	-15.94	-0.57	0.03	0.00	0.01	0.02	-0.11	-4.26	-4.75

Notes: SM = Single Mother. The table presents impacts of removal of grandparent childcare time transfers in terms of mean change in lifetime real wages, mean change in years of experience, mean change in migration measures, and mean change in ex-ante utility with and without migration in the model. Wages and utility measured in thousands of dollars. See text for details on estimation sample and procedure.

start of the model) resulting from the counterfactual scenario and dividing it by α_1, the utility scaling parameter for consumption for women without children. We conduct demographic heterogeneity analyses by assessing impacts for women by grandparent helpfulness type and who were or were not ever single mothers in the baseline simulation. We additionally conduct racial heterogeneity analyses by estimating the impacts for whites and Blacks separately. Finally, we also assess the importance of geography in our model by calculating the WTP for a counterfactual scenario in a version of the model where the fixed moving cost γ_1 is set to infinity, so that no moves will be made. Wages and WTP measures are reported in thousands of dollars.

The removal of grandparents is associated with substantial reductions in wages, with women who have an informal care option working nearly two fewer years and earning over \$60,000 less over their lifecycle. Across the entire sample, the existence of grandparents as a potential source of childcare is associated with close to a year of experience (+ 2.7% off baseline). To put these effects in context with the reduced form estimates earlier in the paper, the child penalty gap was about 22 p.p. smaller for mothers living near their grandparents. Removing grandmothers is thus able to account for about one-eighth of the child penalty we documented, which is reasonable given that the model uses a much less granular measure of 'near' grandparents. Despite Black women having more access to informal care according to our estimates, we find that the removal of informal care does *less* to decrease their experience and earnings, because they have a stronger fertility response than their White counterparts. At the same time, the ex-ante utility of Black women falls by a greater amount due to the higher prevalence of informal care in this subgroup.

Additionally, these results demonstrate that parents' mobility is not only influenced by grandparents but also by regional costs for childcare. Eliminating the pull of the parent location results in increased migration for the same groups of women who see the largest declines in earnings, suggesting that they are substituting from staying in their home location towards either higher paying or lower childcare cost locations when they can no longer take advantage of free relative care in their parent location. As such, the utility cost of the counterfactual is greater when moving is prohibited, and the difference in utility between the world where moving is allowed is larger for more-affected groups. For women who have an informal care option in the baseline simulation, the removal of said options increases the total number of lifecycle moves by 0.07 (6%) and the number of moves between non-parent locations by 0.05 (7.8%).

6.2 Childcare Subsidies

As a final exercise, we conduct a counterfactual where we halve and then remove childcare costs entirely, while breaking down our counterfactual effects by demographics, race, and migration cost scenarios as before. Table 12 reports the results of this exercise. While the introduction of such a policy would clearly have general equilibrium implications on the labor market, we evaluate the policy from a partial equilibrium viewpoint and analyze how it may impact the wages, work, and welfare of an individual woman in the model, which in turn may be informative for the potential impacts of more policy-relevant targeted reductions in childcare costs.

In all cases, these policies increase years of experience, labor mobility, and lifetime wages, with particularly strong effects for women who are ever single parents and larger effects for the complete removal of childcare costs than halving them. Fully subsidizing childcare increases the lifetime earnings of women by about $82,000, which translates to an approximately 10% increase. For comparison, in the reduced form estimates, we saw that the child penalty for women living in low childcare cost states was about 10% lower than for women in high-cost states. Because Black women have more access to informal care than White women and face larger wage reductions from the presence of young children, the childcare cost reductions do markedly less to encourage their labor force participation.

Among all women in our sample, the complete removal of childcare costs raises lifetime moves by 0.03, or roughly 2 percent. Similar to before, the effects on earnings are concentrated among women who are at any point single mothers, and for women who have helpful grandparents the policy increases “Other” moves by 0.06 (9.4%). The effects on earnings and wages are stronger for women who do not have helpful grandparents, since grandparent childcare does crowd out the labor force participation effects of the policies. However, the

Table 12: Effects of Childcare Subsidies

Panel A: Impacts of Halving Childcare Costs

Sample	Wages	Years x	# Moves	Home Moves	Away Moves	Oth. Moves	Fert. f	WTP	WTP, $\gamma_1 = \infty$
All	67.70	1.77	0.01	0.00	0.00	0.01	0.19	8.86	8.18
$\tau^P \neq 0$	30.12	0.94	0.01	0.00	0.00	0.01	0.16	7.74	7.05
$\tau^P = 0$	92.48	2.32	0.00	0.00	0.00	0.01	0.21	9.60	8.93
Never SM	91.86	2.30	0.01	0.00	0.00	0.01	0.21	9.27	8.40
Ever SM	47.46	1.33	0.01	0.00	0.00	0.00	0.17	8.51	8.00
Whites	101.38	2.53	0.02	0.00	0.00	0.02	0.21	10.36	9.22
Blacks	19.43	0.69	-0.01	0.00	0.00	-0.01	0.16	6.81	6.77

Panel B: Impacts of Removing Childcare Costs

Sample	Wages	Years x	# Moves	Home Moves	Away Moves	Oth. Moves	Fert. f	WTP	WTP, $\gamma_1 = \infty$
All	82.39	2.56	0.03	0.00	0.01	0.03	0.50	25.55	23.88
$\tau^P \neq 0$	36.07	1.35	0.08	0.00	0.02	0.06	0.36	19.29	17.13
$\tau^P = 0$	112.92	3.35	0.00	-0.01	0.00	0.01	0.59	29.67	28.33
Never SM	113.52	3.26	0.04	0.00	0.01	0.03	0.58	27.28	25.30
Ever SM	56.30	1.97	0.03	0.00	0.00	0.03	0.43	24.09	22.72
Whites	121.07	3.45	0.05	0.00	0.01	0.04	0.56	30.32	27.70
Blacks	26.94	1.27	0.01	0.00	0.00	0.01	0.41	18.99	18.66

Notes: SM = Single Mother. The table presents impacts of counterfactual scenarios in terms of mean change in lifetime real wages, mean change in years of experience, mean change in number of various moves, and changes in ex-ante utility with and without migration in the model. Wages and utility measured in thousands of dollars. See text for details on estimation sample and procedure.

migration effects are largest for women who *do* have helpful grandparents, since it is these women for whom the geographic constraint induced by grandparent childcare applies.

The elasticities of fertility among model agents in response to counterfactual policies are in line with other literature entries. Specifically, the specification in which we halve childcare costs for 5 years is equivalent to a transfer of around $25,000 and increases fertility by 0.19 relative to the model baseline. This elasticity is similar to one found by Zhou [2022], who estimates that a $30,000 "baby bonus" would raise US fertility rates by about 0.15 points. We also compare our elasticity to Haan and Wrohlich [2011], who estimate a roughly 4.6% increase in fertility in response to a ∼$500 transfer. Our estimated elasticity for a similar transfer is 2%, which may be lower due to different country and time contexts. The fertility responses to the full subsidy suggest that women would have, roughly, an additional 0.4 children on average if childcare costs were removed entirely. Labor force participation and earnings increase despite these increases in childbearing.

We find that ignoring labor mobility may understate the welfare benefits of childcare policies. Across all individuals, the average willingness to pay for the full removal of childcare costs at age 22 is approximately $25,550. Without migration in the model, however, the WTP falls by around $1,700. Unsurprisingly, the willingness to pay for the policies is considerably higher for women that benefit more from them, such as single mothers, Whites (who, recall, have fewer helpful grandparents than Blacks), and women with parents who do not provide childcare. At the same time, the migration mechanism matters more for the groups that more often receive grandparent assistance — compared to the WTP in the world without migration, allowing for migration increases WTP by over 12% for women with helpful grandparents.

Table 13: Decomposition of Childcare Subsidy Wage Effect

Sample	Total Effect	Share h	Share x	Share f	Share ℓ
All	82.39	0.74	0.26	-0.01	0.03
$\tau^P \neq 0$	36.07	0.65	0.34	-0.03	0.06
$\tau^P = 0$	112.92	0.76	0.24	-0.01	0.03
Never SM	113.52	0.80	0.19	-0.01	0.03
Ever SM	56.30	0.63	0.37	-0.02	0.04
Whites	121.07	0.77	0.23	-0.01	0.03
Blacks	26.94	0.53	0.46	-0.06	0.03

Notes: Table present increases in real wages following full childcare subsidy counterfactual and decomposes the sources of these changes into shares that can be exclusively attributed to labor supply (h), experience (x), fertility (f), and location choices (ℓ). Wages measured in thousands of dollars. See text for details on decomposition and estimation procedure.

We also assess the importance of migration in our model by decomposing the wage impacts of the full childcare subsidization into four sources: increased labor force participation, increased experience, fertility adjustments, and movement to higher-paying locations. We run this decomposition by comparing each observation of our baseline and counterfactual simulated data: if a given observation works in our baseline simulation and does not work in the counterfactual (or vice-versa), then we attribute all the change in wages for that observation stem from changes in labor force participation.[18] If the observation does work in both the simulations, we use the estimated wage equation in conjunction with the simulations to determine the portion of the wage difference that comes from changes in experience, fertility, and location effects. Specifically, call the difference in real wages between the two simulations

$$\Delta w_r \equiv \frac{w_n'}{\kappa_{\ell'}} - \frac{w_n}{\kappa_\ell},$$

where w_n denotes nominal wages, κ_ℓ denotes living costs, and apostrophes indicate counter-

[18]The choice to work in itself may be influenced by other preceding behavioral adjustments that altered fertility or experience in a given period. Accounting for the full interaction of all these choices would be mathematically intractable, so we focus on each behavioral margin in isolation.

factual wages and locations. We determine the portion of Δw_r attributable to experience by computing what the difference in real wages between the baseline and counterfactual simulation would have been if *only* experience was changed to its counterfactual value — calling this difference Δw_r^e, the share attributable to experience is then $\Delta w_r^e/\Delta w_r$. We conduct the same exercise to assess the role of fertility and location wage effects, and then we add to the location share the role of different living costs by assessing the counterfactual real wage difference if w_n' was held constant but $\kappa_{\ell'}$ was switched to κ_ℓ.

We present the results of this decomposition in Table 13 and generally find that location has a limited role in the wage effects of the policies. Approximately 3 percent of the wage effect across the sample is due to women locating in higher-wage locations — for women who have an informal care option and thus have the largest migratory response to the policies, the corresponding share is 6 percent. This may seem inconsistent with the substantial role geography plays in informing the *welfare* benefits of childcare policy found earlier, but these two findings are reconciled by the fact that non-pecuniary factors (i.e. idiosyncratic utility shocks) play a large role in migration decisions. As a result, policies that relax geographic constraints can meaningfully impact agent utility despite only modestly affecting wages.

7 Conclusion

This paper studies how childcare costs, the location of extended family, and fertility events influence both the labor force attachment and labor mobility of women in the United States. We document trends in the data that suggest that the need for informal childcare exerts considerable pull for U.S. women, especially those without a spouse. This manifests in women being substantially more likely to move back to their home location when faced with an imminent fertility event preferring to move to lower-childcare-cost states if they have children to take care of. These short-run behavioral margins are complemented by long-run reductions in the child earnings penalty for women who have nearby grandparents.

These analyses provide evidence consistent with past research that documents that the presence of grandparents and informal care meaningfully impacts the labor market outcomes of women in the United States. Our primary contribution comes from taking seriously the choice to locate nearby to grandparents in the first place. If women are sacrificing labor market opportunities by locating in places where they can use informal care, then policies that encourage substitution from informal to formal care need not be wage or welfare-neutral, as they may enable women to move to more productive or preferred locations.

We present a tractable model of dynamic labor force participation and migration that aims to capture the geographic constraints imposed by childcare costs and grandparent locations that U.S. women face. The presence of grandparents reduces childcare costs and thus reservation wages, allowing women to maintain their participation in the labor force and to continue building work experience that will subsequently raise wages for the remainder of their life. However, these benefits only apply if women are located in the same place as their grandparents, which is a notable constraint given the extent to which migration plays a role in wage growth [Kennan and Walker, 2011]. We do not impose that location decisions are one-shot as in García-Morán and Kuehn [2017], however: women may leave their parent's location and then move back when they know that a fertility event is imminent.

The assumption that women only have one child at a time means that our model almost certainly understates childcare costs and the potential effects of childcare subsidy policies on labor force participation, experience, and wages. Moreover, the discretization of geography into nine locations means that we may be suppressing the role that geography plays in wages, which may also have implications for our counterfactual policy predictions. Allowing for a richer geographic structure and potentially an urban/rural distinction while retaining computational tractability in the model may be desirable. Extending the model to account for additional unobserved heterogeneity in wages such that the agents as well as their spouses differ in fixed effects and, possibly, location-specific match effects may also be worthwhile.

Nonetheless, the model is able to fit women's labor supply and migration decisions well. We estimate meaningful racial differences in rates of informal care use. For those women who do have access to informal care, the informal care option plays a large role in encouraging labor force participation and increasing lifetime earnings at the cost of constraining where these women choose to work. As a result, policies that reduce the cost of childcare substantially increase the labor mobility of these women, and a non-trivial component of the increase in earnings enjoyed by them following the policies comes from their being able to locate to labor markets with higher real wages. Our findings make clear that the non-pecuniary factors in location decisions confer considerable welfare benefits, and childcare subsidies reduce mobility frictions. As such, analyses that do not consider the welfare consequences of increased mobility will understate the benefits of childcare policies.

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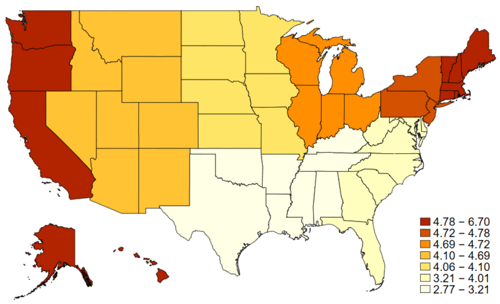
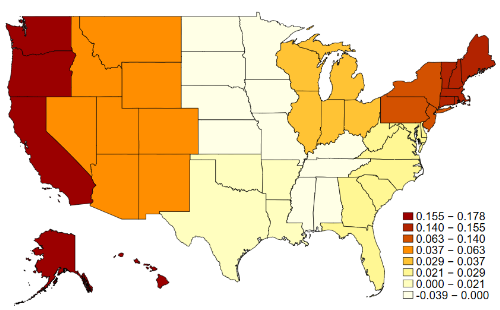
8 APPENDIX – FOR ONLINE PUBLICATION

A Supplementary Figures and Tables

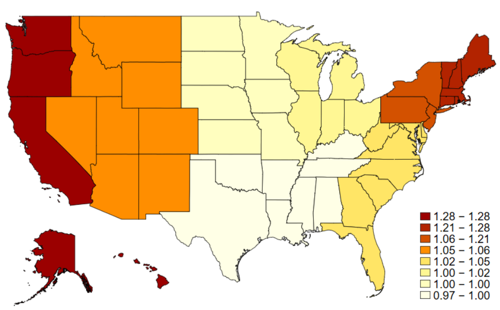
Figure A.1: Division Characteristics



(a) Childcare Costs



(b) Wage Effects



(c) Costs of Living

Notes: Data on childcare costs from the BLS National Database of Childcare Prices. Units measured in 1000s of 2012 dollars. Wage effects from Mincerian regressions for men in American Community Survey, and costs of living from ACCRA.

Table A.1: Fertility Characteristics of Women by Moving Status

	Non-Mover, Home	Mover, Home	Non-Home	All
Number of Children	1.235	0.910	1.130	1.200
	(1.279)	(1.193)	(1.274)	(1.278)
Age of Youngest Child	5.163	3.905	5.346	5.191
	(4.578)	(4.120)	(4.679)	(4.600)
First Pregnancy	0.0267	0.0427	0.0254	0.0265
	(0.161)	(0.202)	(0.157)	(0.161)
Child, Age 1-5	0.329	0.317	0.292	0.318
	(0.470)	(0.465)	(0.455)	(0.466)
Observations	2,412,222	35,710	901,049	3,384,074

Notes: This table reports mean and s.d. (in parentheses) of fertility characteristics of US-native women aged 22-40 in the 2006-2019 ACS who completed at least one year of high school. Col. 1 includes women living in their birth state in the prior and current year. Col. 2 includes women living in a non-birth state in the prior year and in their birth state in the current year. Col. 3 includes women living in a non-birth state in the prior and current year. Col. 4 includes all women in the sample.

Table A.2: Effects of Later Pregnancy on Home Migration Probability (HMP)

	(1)	(2)	(3)	(4)	(5)	(6)
	All	Non-Married	Married	White	Black	Other Races
	Mean = 3.57	Mean = 3.29	Mean = 3.84	Mean = 3.70	Mean = 3.24	Mean = 3.52
Second or More Pregnancy	-0.115	-0.250	-0.103	0.0469	-0.138	0.250
	(0.116)	(0.243)	(0.131)	(0.133)	(0.333)	(0.322)
Observations	933,489	441,608	491,881	707,994	94,990	105,107
Adjusted R^2	0.051	0.048	0.061	0.058	0.079	0.125

Notes: The sample includes US-native-born women aged 22-40 in the 2006-2019 ACS who completed at least one year of high school and were not located in birth state or birth state of their husband if married the previous year. Additional controls include fixed effects for birth state, current state, and previous state, and calendar year, a quadratic in age, indicators for education (HS drop out (omitted), HS, Some College, College, More than College), indicator for marital status, and indicators for race (White (omitted), Black, Non-White/Black). Second or More Pregnancy indicator defined by presence of a child less than one year old while being more than one own child of the respondent in the household. Regressions weighted by sampling weights and robust standard errors in parentheses.$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

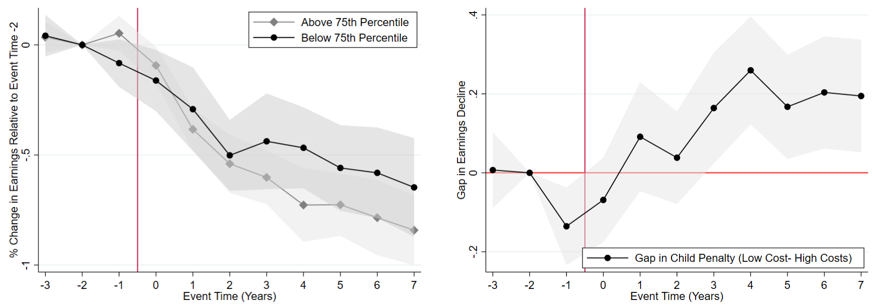
Table A.3: Effects of Children and Location on Hours Worked

	(1) All	(2) All	(3) Non-Married	(4) Married
Young Child	-1.976***	-3.751***	-2.248***	-8.676***
	(0.0548)	(0.0766)	(0.111)	(0.0801)
Married	-0.791***	-0.774***		
	(0.0344)	(0.0344)		
Young Child× Married	-5.310***	-5.307***		
	(0.0673)	(0.0673)		
CC Cost std.	0.0386	0.0615	-0.0953	0.172+
	(0.0668)	(0.0673)	(0.0972)	(0.0928)
Young Child × CC Cost std.		-0.0881**	-0.491***	0.0969*
		(0.0302)	(0.0553)	(0.0382)
Home State	0.485***	-0.231***	-1.093***	1.306***
	(0.0355)	(0.0399)	(0.0533)	(0.0611)
Young Child × Home State		2.367***	0.916***	1.783***
		(0.0711)	(0.126)	(0.0912)
Observations	2,402,312	2,402,312	1,083,345	1,318,967
Adjusted R^2	0.099	0.100	0.105	0.103

Notes: The outcome of interest is usual hours worked in the previous year. All variables (age of child, child care costs in-state , indicator for living in home state) are measured in the year prior to the survey. CC Costs (standardized: mean=0, SD = 1) refers to the average weekly costs for toddler center-based care in the state of residence in the year prior to the interview. The sample includes US-native-born women aged 22-40 in the 2006-2019 ACS who completed at least one year of high school. Additional controls include fixed effects for birth state, state in prior year, and calendar year, a quadratic in age, indicators for education (HS drop out (omitted), HS, Some College, College, More than College), indicator for marital status, and indicators for race (White (omitted), Black, Non-White/Black). Young Child indicator defined as presence of own child aged at most four in household. Regressions weighted by sampling weights and robust standard errors in parentheses.$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

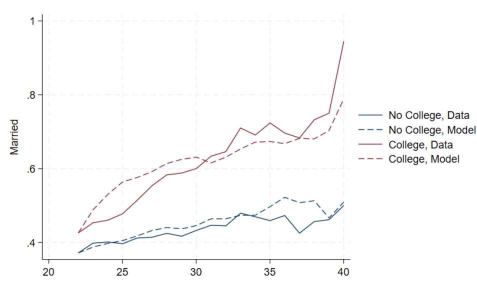
Figure A.2: Child Penalty for Women Living in High or Low Childcare Cost States

Panel A   Panel B

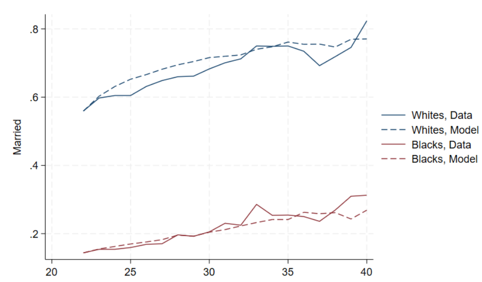


Notes: Figure A.2A (left) plots coefficients and 95% confidence intervals from event studies of earnings on indicators for years surrounding a woman's first birth for both women who live in the high or low childcare cost states, defined as above or below the 75th percentile of the national distribution of prices. The units are percent changes (0 to 1) in earnings relative to the year prior to birth. The regression includes controls for age of mother at first birth, year of birth and county-state, as well as including men as a control group. Figure A.2B (right) calculates the gap in the percent decline for those in high-cost relative to those in low-cost states and reports 10% confidence intervals for a test of the null that this gap is equal to zero.

Figure A.3: Model Fit — Marriage Life-Cycle Profiles



(a) By Education



(b) By Race

Notes: Figure presents model fit of marriage rates over lifecycle for women in PSID analysis sample and in data simulated from model. Probabilities estimated separately for women with and without a college degree and depend on marital status, race, pregnancy, presence of young children, a cubic in age, and spouse wage type. See text for details on sample construction.

Table A.4: Divisional Groupings of States

New England (NE):	Connecticut, Maine, Massachusetts, New Hampshire, Rhode Island, Vermont.
Mid-Atlantic (MA):	New Jersey, New York, Pennsylvania.
East North Central (ENC):	Illinois, Indiana, Michigan, Ohio, Wisconsin.
West North Central (WNC):	Iowa, Kansas, Minnesota, Missouri, Nebraska, North Dakota, South Dakota.
South Atlantic (SA):	Delaware, Florida, Georgia, Maryland, North Carolina, South Carolina, Virginia, District of Columbia, West Virginia.
East South Central (ESC):	Alabama, Kentucky, Mississippi, Tennessee.
West South Central (WSC):	Arkansas, Louisiana, Oklahoma, Texas.
Mountain (MO):	Arizona, Colorado, Idaho, Montana, Nevada, New Mexico, Utah, Wyoming.
Pacific (PA):	Alaska, California, Hawaii, Oregon, Washington.

Notes: This table lists which states are contained in each Census region, which is the primary geographic unit in the structural model.

Table A.5: Observations by Age

Age	All	Whites	Blacks
22	932	549	383
23	932	549	383
24	932	549	383
25	932	549	383
26	854	510	344
27	789	478	311
28	718	438	280
29	648	393	255
30	587	353	234
31	518	314	204
32	456	278	178
33	402	248	154
34	365	227	138
35	306	192	114
36	250	162	88
37	202	130	72
38	148	96	52
39	101	59	42
40	50	34	16
Total:	**10,122**	**6,108**	**4,014**

Notes: Table presents number of individuals observed at each age in PSID analysis sample. See text for details on sample construction.

Table A.6: Summary Statistics of PSID Estimation Sample

Sample	All		White		Black	
Age	≤ 30	> 30	≤ 30	> 30	≤ 30	> 30
LFP Rate	53.56	51.11	52.24	48.97	55.51	54.63
	(49.88)	(50.00)	(49.96)	(50.00)	(49.70)	(49.81)
Years of Experience	4.61	8.69	4.28	8.36	5.10	9.23
	(2.64)	(4.32)	(2.76)	(4.52)	(2.38)	(3.92)
Hourly Wage	15.23	17.66	16.46	18.66	13.53	16.19
	(6.97)	(7.67)	(7.16)	(7.64)	(6.30)	(7.48)
Share Married	43.94	54.82	62.29	72.87	16.81	25.14
	(49.63)	(49.78)	(48.47)	(44.47)	(37.40)	(43.40)
Young Child Present	50.31	32.59	50.50	36.21	50.03	26.65
	(50.00)	(46.88)	(50.00)	(48.07)	(50.01)	(44.24)
College Share	32.43	39.21	41.32	48.10	19.28	24.57
	(46.81)	(48.83)	(49.25)	(49.98)	(39.46)	(43.07)
Observations	7324	2798	4368	1740	2956	1058

(a) Demographic and Economic Statistics

Sample	All	White	Black
Annual Migration Rate	4.04	4.71	3.01
	(19.68)	(21.19)	(17.09)
With Children	3.41	4.11	2.30
	(18.16)	(19.85)	(15.0)
If Married	3.55	3.79	2.26
	(18.5)	(19.11)	(14.86)
Ever Migrated	26.97	31.02	20.79
	(44.38)	(46.26)	(40.58)
Share of Moves to ℓ^P	30.03	30.42	29.09
	(45.9)	(46.09)	(45.63)
N	10122	6108	4014

(b) Migration Statistics

Notes: Standard deviations in parentheses. Data from 2001-2019 biennial waves of PSID. Table A.6a presents demographic statistics for analysis sample, broken down by race and age at observation. Table A.6b presents migration statistics for the estimation sample, broken down by race. See text for details on sample restrictions.

B Data and Mathematical Appendix

B.1 Model Solution Details

The steps for solving the model through backward induction are as follows:

1. Solve for cutoff values of ε_w that govern labor force participation for the terminal age-65 period, where continuation values are zero by construction.

2. Using properties of the normal distribution, solve for *expected* utility $\mathbb{E}_{\varepsilon_w}[V_{65}^2(\Omega, \ell)]$ following the optimal labor supply decision in the age-65 state space.

3. Apply the type-1 extreme value formula to construct the agent's expected utility from choosing their optimal next-period location at age 64:

$$\mathbb{E}_{\zeta_{\ell'}}[V_{64}^1(\Omega, \ell; h)] = \bar{\gamma} + \log\left(\sum_{\ell'} \exp\left(\beta \sum_{\Omega'} \mathbb{E}_{\varepsilon_f}[V_{65}^1(\Omega', \ell')]\mathbf{Pr}(\Omega'|\Omega, h, \ell') - \Delta(\Omega, \ell')\mathbb{1}\{\ell' \neq \ell\}\right)\right)$$

   where $\bar{\gamma}$ is the Euler-Mascheroni constant. This gives continuation values for all possible combinations of state space and labor supply decisions for the age-64 period. If the agent is less than 40 years old, computing the expectation of V_1 additionally includes solving for cutoff values of ε_f that govern fertility decisions and applying the inverse Mills ratio to determine how happy the agent expects to be from making their fertility decision.

4. With continuation values in hand, compute cutoff values of ε for the age-64 period.

5. Repeat steps 2-4 through ages 63 to 22, at which point the model is solved.

This section details the procedure for computing these reservation levels of transient wage components ε_w and expected value functions when solving the model using the backward induction method.

There are three stages of life in which households are making decisions: the post-children period (46-65), the post-fertility period (41-45), and the fertility period. The agents in our model can move at any point and the marital state at age 40 is assumed to be maintained for the remainder of the life cycle. We focus on reservation wages for age 65 and 64 here to build intuition about decisions without young children and for age 45 for decisions with young children; the procedure for earlier ages is identical after accounting for uncertainty over realizations of marriage and fertility shocks.

In the post-children period, households no longer ever have young children (i.e., $a_c = \emptyset$). The agent makes a decision of whether the wife should work or not work, which will depend on the realization of the ε shock. At age 65, given the other elements of the state space Ω,[19] flow utility from working and not working u^1_{65}, u^0_{65} is given by

$$u^1_{65}(\Omega,\ell) = \alpha_1(w_S(\Omega,\ell)) + \alpha_1 \exp(\beta_0 + \beta_1 e + \beta_2 x + \beta_3 x^2 + \mu + \eta^\ell + \varepsilon_w) + \alpha_3 \mathbb{1}(p=0) + \alpha_4 \mathbb{1}(\ell = \ell^P)$$

$$u^0_{65}(\Omega,\ell) = (\alpha_1 + \alpha_c)(w_S(\Omega,\ell)) + \alpha_2 + \alpha_e e + \alpha_x x + \alpha_\mu \mathbb{1}\{\mu = \mu^H\} + \alpha_3 \mathbb{1}(p=1) + \alpha_4 \mathbb{1}(\ell = \ell^P)$$

$w_S(\Omega,\ell)$ is the realization of spousal income, conditional on spousal characteristics contained within (Ω,ℓ). p is the participation decision the previous period which determines if the person receives the switching cost α_3. We ignore costs of living differences and amenities in this formulation, but these can easily be accounted for by dividing α_1 and α_c by the relevant κ^ℓ or by adding the relevant $\boldsymbol{\alpha_\Gamma}$.

Because agents are finitely lived, $V_{66} = 0$ and the value function in the terminal period is then

$$V^2_{65}(\Omega_{65},\ell) = \max\left\{u^1_{65}(\Omega,\ell), u^0_{65}(\Omega,\ell)\right\}$$

Participation is governed by the following:

$$h = \begin{cases} 1 & \varepsilon_{w,65} > \varepsilon^{**}_{w,65}(\Omega,\ell) \\ 0 & \text{otherwise} \end{cases}$$

$$\begin{aligned} \varepsilon^{**}_{w,65}(\Omega,\ell) \quad \equiv \quad & > \log\left(\frac{\alpha_2 + \alpha_e e + \alpha_x x + \alpha_c w_S(\Omega,\ell) + \alpha_3\big(\mathbb{1}(p=1) - \mathbb{1}(p=0)\big)}{\alpha_1}\right) \\ & - \underbrace{(\beta_0 + \beta_1 e + \beta_2 x + \beta_3 x^2 + \eta^\ell)}_{G_{65}(\Omega,\ell)} \end{aligned}$$

We can then use this decision rule to calculate the expected utility following the optimal

[19] For this section, we also subsume the fertility decision f into Ω, since we know that $f = 0$ in later stages of the life cycle.

age-65 labor supply choice. That is,

$$
\begin{aligned}
\mathbb{E}_{\varepsilon_w}[V^2_{65}(\Omega,\ell)] &= \mathbf{Pr}\big(\varepsilon_{w,65} > \varepsilon^{**}_{w,65}\big)\mathbb{E}[u^1_{65}(\Omega,\ell)|\varepsilon_{w,65} > \varepsilon^{**}_{w,65}] \\
&\quad + \mathbf{Pr}\big(\varepsilon_{w,65} < \varepsilon^{**}_{w,65}\big)\mathbb{E}[u^0_{65}(\Omega,\ell)|\varepsilon_{w,65} < \varepsilon^{**}_{w,65}] \\
&= \alpha_1 w_S + \alpha_4 \mathbb{1}(\ell = \ell^P) \\
&\quad + \mathbf{Pr}\big(\varepsilon_{w,65} > \varepsilon^{**}_{w,65}\big)\alpha_3 \mathbb{1}[p=0] \\
&\quad + \mathbf{Pr}\big(e^{\varepsilon_{w,65}} > e^{\varepsilon^{**}_{w,65}}\big)\alpha_1 \mathbb{E}(e^{\varepsilon_{w,65}}|e^{\varepsilon_{w,65}} > e^{\varepsilon^{**}_{w,65}})\exp(G_{65}(\Omega,\ell)) \\
&\quad + \mathbf{Pr}\big(\varepsilon_{w,65} < \varepsilon^{**}_{w,65}\big)\big(\alpha_2 + \alpha_e e + \alpha_x x + \alpha_c w_S(\Omega,\ell) + \alpha_3 \mathbb{1}[p=1]\big) \\
&= \alpha_1 w_S + \alpha_4 \mathbb{1}(\ell = \ell^P) \\
&\quad + \left[1 - \Phi\left(\frac{\varepsilon^{**}_{w,65}}{\sigma_w}\right)\right]\alpha_3 \mathbb{1}[p=0] \\
&\quad + \left[1 - \Phi\left(\frac{\varepsilon^{**}_{w,65} - \sigma^2_w}{\sigma_w}\right)\right]\alpha_1 e^{0.5\sigma^2_w + G_{65}(\Omega,\ell)} \\
&\quad + \Phi\left(\frac{\varepsilon^{**}_{w,65}}{\sigma_w}\right)\big(\alpha_2 + \alpha_e e + \alpha_x x + \alpha_c w_S(\Omega,\ell) + \alpha_3 \mathbb{1}[p=1]\big).
\end{aligned}
$$

Moving back to period 64, the agent will end the period by realizing their location preference shocks and choosing their optimal age-64 location, ℓ', conditional on their current state (Ω), the participation decision made at the beginning of period 64 (h), and their current location (ℓ):

$$
\ell' = \arg\max_{k \in \mathbb{N}^\ell} \left(\mathbb{1}(k \neq \ell) \times \underbrace{(\gamma_0 + \gamma_1 e + \gamma_3 m + \gamma_4 N^k + \gamma_5 a)}_{\Delta_k} + \beta \left(\mathbb{E}_{\varepsilon_w} \sum_{\Omega'} [V^2_{65}(\Omega', k)] \mathbf{Pr}(\Omega'|\Omega, h, k) \right) + \zeta_k \right)
$$

With the assumption that these shocks are drawn from the type-1 extreme value location with a variance normalized to 1, we can calculate the probability of choosing location ℓ':

$$
Pr(\ell_{64} = \ell'|\Omega,\ell,h) = \frac{\exp\left(\mathbb{1}(\ell' \neq \ell) \times \Delta_{\ell'} + \beta\left(\mathbb{E}_{\varepsilon_w}\sum_{\Omega'}[V^2_{65}(\Omega',\ell')]\mathbf{Pr}(\Omega'|\Omega,h,\ell')\right)\right)}{\sum_k \exp\left(\mathbb{1}(k \neq \ell) \times \Delta_k + \beta\left(\mathbb{E}_{\varepsilon_w}\sum_{\Omega'}[V^2_{65}(\Omega',k)]\mathbf{Pr}(\Omega'|\Omega,h,k)\right)\right)}
$$

and the expected utility following the optimal decision as:

$$
\mathbb{E}_{\zeta_{\ell'}}[V^3_{64}(\Omega,\ell;h)] = \bar{\gamma} + \log\left(\sum_{\ell'} \exp\left(\beta \sum_{\Omega'} \mathbb{E}_{\varepsilon_w}[V^2_{65}(\Omega',\ell')]\mathbf{Pr}(\Omega'|\Omega,h,\ell') - \Delta_{\ell'}\mathbb{1}\{\ell' \neq \ell\}\right)\right).
$$

This then allows us to express the age-64 value function as:

$$
V_{64}(\Omega,\ell) = \max\left\{u^1_{64}(\Omega,\ell) + \mathbb{E}_{\zeta_{\ell'}}[V^3_{64}(\Omega,\ell;1)],\, u^0_{64}(\Omega,\ell) + \mathbb{E}_{\zeta_{\ell'}}[V^3_{64}(\Omega,\ell;0)]\right\},
$$

where $u^1_{64}(\Omega,\ell)$ and $u^0_{64}(\Omega,\ell)$ are defined comparably to their age-65 counterparts. The decision rule for working given $\varepsilon_{w,64}$ is then given by:

$$h = \begin{cases} 1 & \varepsilon_{w,64} > \varepsilon^{**}_{w,64}(\Omega,\ell) \\ 0 & \text{otherwise} \end{cases}$$

$$\begin{aligned}\varepsilon^{**}_{w,64}(\Omega,\ell) \quad \equiv \quad & \log\Bigg(\frac{\alpha_2}{\alpha_1} + \frac{\alpha_e}{\alpha_1}e + \frac{\alpha_x}{\alpha_1}x + \frac{\alpha_c}{\alpha_1}w_S(\Omega,\ell) + \frac{\alpha_3}{\alpha_1}\left(\mathbb{1}(p=1) - \mathbb{1}(p=0)\right) \\ & + \frac{1}{\alpha_1}\mathbb{E}_{\zeta_{\ell'}}\left([V^3_{64}(\Omega,\ell;0)] - \mathbb{E}_{\zeta_{\ell'}}[V^3_{64}(\Omega,\ell;1)]\right)\Bigg) - G_{64}(\Omega,\ell)\end{aligned}$$

This then allows us to express the expected utility following the age-64 labor supply choice as follows:

$$\begin{aligned}\mathbb{E}_{\varepsilon_{w,64}}[V^2_{64}(\Omega,\ell)] \quad = \quad & \alpha_1 w_S + \alpha_4\mathbb{1}(\ell = \ell^P) \\ & + \left[1 - \Phi\left(\frac{\varepsilon^{**}_{w,64}}{\sigma_w}\right)\right]\Big(\alpha_3\mathbb{1}[p=0] + \mathbb{E}_{\zeta_{\ell'}}[V^3_{64}(\Omega,\ell;1)]\Big) \\ & + \left[1 - \Phi\left(\frac{\varepsilon^{**}_{w,64} - \sigma^2_w}{\sigma_w}\right)\right]\alpha_1 e^{0.5\sigma^2_w + G_{64}(\Omega,\ell)} \\ & + \Phi\left(\frac{\varepsilon^{**}_{w,64}}{\sigma_w}\right)\Big(\alpha_2 + \alpha_e e + \alpha_x x + \alpha_c w_S(\Omega,\ell) + \alpha_3\mathbb{1}[p=1] + \mathbb{E}_{\zeta_{\ell'}}[V^3_{64}(\Omega,\ell;0)]\Big),\end{aligned}$$

which in turn allows us to compute age-63 continuation values, and so on. This continues recursively in the same fashion until age 45 (i.e., the last year in which an agent may have a young child). For those without children at 45, the decision process is unchanged. For those with a child, they now have the costs of childcare to consider in their labor supply decision and the location of parents as a source of cheaper care to consider in their location decision.

For a person with a young child, given the other elements of the state space Ω, flow utility from working and not working u^1, u^0 is given by:

$$\begin{aligned}u^1(\Omega,\ell,a_c \neq \emptyset) \quad = \quad & \alpha_5\Big(w_S(\Omega,\ell) + \exp\left(\beta_0 + \beta_1 e + \beta_2 x + \beta_3 x^2 + \eta^\ell + \varepsilon_w\right) \\ & -\delta_\ell\big(1 - \tau_{pm}\mathbb{1}(\ell = \ell^P) - \tau_s m\big)\Big) + \alpha_3\mathbb{1}(p=0) + \alpha_7\mathbb{1}(\ell = \ell^P); \\ u^0(\Omega,\ell,a_c \neq \emptyset) \quad = \quad & (\alpha_5 + \alpha_c)(w_S(\Omega,\ell)) + \alpha_6 + \alpha_e e + \alpha_x x + \alpha_3\mathbb{1}(p=1) + \alpha_7\mathbb{1}(\ell = \ell^P).\end{aligned}$$

At age 45, the expected utility following the optimal location decision, $\mathbb{E}_{\zeta_{\ell'}}[V^3_{45}(\Omega,\ell;h)]$ follows the same general form as the previously described expected utility in period 64.

This, combined with the flow utility, gives us the following participation decision rule:

$$h = \begin{cases} 1 & \varepsilon_{w,45} > \varepsilon^{**}_{w,45}(\Omega, \ell) \\ 0 & \text{otherwise} \end{cases}$$

$$\begin{aligned} \varepsilon^{**}_{w,45}(\Omega, \ell) \quad \equiv \quad & \log\Bigg(\frac{\alpha_6}{\alpha_5} + \frac{\alpha_e}{\alpha_5}e + \frac{\alpha_x}{\alpha_5}x + \frac{\alpha_c}{\alpha_5}w_S(\Omega, \ell) + \frac{\alpha_3}{\alpha_5}\left(\mathbb{1}(p=1) - \mathbb{1}(p=0)\right) \\ & + \frac{1}{\alpha_5}\mathbb{E}_{\zeta_{\ell'}}\left([V^3_{45}(\Omega, \ell; 0)] - \mathbb{E}_{\zeta_{\ell'}}[V^3_{45}(\Omega, \ell; 1)]\right) + \delta_\ell\big(1 - \tau_{pm}\mathbb{1}(\ell = \ell^P) - \tau_s m\big)\Big)\Bigg) - G_{45}(\Omega, \ell); \end{aligned}$$

There are two notable differences in the reservation wage for women with children relative to those without. First, the parameters governing valuation of consumption (α_5) and the value of leisure (α_6) differ, potentially raising the reservation wage relative to non-mothers if α_6 is higher than α_2 or lowering the reservation wage if α_5 is higher than α_1. Second, the added cost of childcare δ^ℓ will raise the reservation wage for mothers.

This then allows us to express the expected utility following the age-45 labor supply choice as follows:

$$\begin{aligned} \mathbb{E}_{\varepsilon_{w,45}}[V^2_{45}(\Omega, \ell)] \quad = \quad & \alpha_5 w_S + \alpha_7 \mathbb{1}(\ell = \ell^P) \\ & + \left[1 - \Phi\left(\frac{\varepsilon^{**}_{w,45}}{\sigma_w}\right)\right]\left(\alpha_3\mathbb{1}[p=0] - \alpha_5\delta_\ell\big(1 - \tau_{pm}\mathbb{1}(\ell = \ell^P) - \tau_s m\big) + \mathbb{E}_{\zeta_{\ell'}}[V^3_{45}(\Omega, \ell; 1)]\right) \\ & + \left[1 - \Phi\left(\frac{\varepsilon^{**}_{w,45} - \sigma^2_w}{\sigma_w}\right)\right]\alpha_5 e^{0.5\sigma^2_w + G_{45}(\Omega, \ell)} \\ & + \Phi\left(\frac{\varepsilon^{**}_{w,45}}{\sigma_w}\right)\left(\alpha_6 + \alpha_e e + \alpha_x x + \alpha_c w_S(\Omega, \ell) + \alpha_3\mathbb{1}[p=1] + \mathbb{E}_{\zeta_{\ell'}}[V^3_{45}(\Omega, \ell; 0)]\right), \end{aligned}$$

which in turn allows us to compute age-44 continuation values. The location choice decision at age 44 takes the same form as previously, though with the addition of a component of the moving cost for parents with a young child and with an additional component of expected future utility (i.e., the future childcare costs) varying by location.

The process continues in this manner until age 40, at which fertility decisions and marriage shocks enter the model. At age 40, the woman makes a fertility decision governed by

$$f = \begin{cases} 1 & \varepsilon_{f,40} > \varepsilon^{**}_{f,40} \\ 0 & \text{otherwise} \end{cases}$$

$$\varepsilon^{**}_{f,40} \quad \equiv \quad \mathbb{E}_{\varepsilon_{w,40}}[V^2_{40}(\Omega, \ell; 0)] - \mathbb{E}_{\varepsilon_{w,40}}[V^2_{40}(\Omega, \ell; 1)] - (\theta_1 + \theta_2 a + \theta_3 m + \theta_4 am + \theta_5 e)$$

The form of the $\mathbb{E}_{\varepsilon_{w,40}}[V_{40}^2]$ terms follows immediately from derivations above. Applying the inverse Mills ratio leads to the following expression for the ex-ante utility derived from solving this fertility decision:

$$\begin{aligned}\mathbb{E}_{\varepsilon_{f,40}} V_{40}^1(\Omega,\ell) \quad = \quad & \left[1-\Phi\left(\frac{\varepsilon_{f,40}^{**}}{\sigma_f}\right)\right]\left([V_{40}^2(\Omega,\ell;1)]+\theta_1+\theta_2 a+\theta_3 m+\theta_4 am+\theta_5 e+M(\varepsilon_{f,40}^{**})\right)\\ & +\Phi\left(\frac{\varepsilon_{f,40}^{**}}{\sigma_f}\right)\left([V_{40}^2(\Omega,\ell;0)]\right),\end{aligned}$$

where $M()$ denotes the inverse Mills ratio. We then have the following expression for the expected utility gained from solving the age-39 location choice problem:

$$\mathbb{E}_{\zeta_{\ell'}}[V_{39}^3(\Omega,\ell;f,h)] = \bar{\gamma} + \log\left(\sum_{\ell'} \exp\left(\beta \sum_{\Omega'} \mathbb{E}_{\varepsilon_f}[V_{40}^1(\Omega',\ell')]\mathbf{Pr}(\Omega'|\Omega,f,h,\ell') - \Delta_{\ell'}\mathbb{1}\{\ell' \neq \ell\}\right)\right).$$

This expression is largely equivalent to its age-64 counterpart but now considers the expectation of V_{39}^1 instead of V_{39}^2, and transitions between Ω states will now include shocks to marital status. Otherwise, the decision problems are unchanged, and the remainder of the model can be solved in a similar fashion until reaching age 22.

B.2 Estimation Sample Details

When coding the location of the grandparents, we use the state of both parents of the PSID respondent (which may be the wife or the husband) if both are living in the same state (which is the case the overwhelming majority of the time). If the grandparents are living in different states or if the grandfather's location is missing, we use the location of the grandmother, and we use the location of the grandfather if the grandmother's location is missing. Grandparents are assumed to be living in the agent's home location if the location of both the grandmother and the grandfather are missing[20]. The parent location variable in our model is treated as static so as to avoid having to consider potential parental moves when evaluating continuation values, which would be computationally prohibitive. So that our data is consistent with this assumption, we take the modal parent location for an individual as the permanent parent location.[21]

[20] Among observations with non-missing parent locations, this is true over 85% of the time.

[21] We view this simplification as unlikely to meaningfully change our results, as the parents of the women in our PSID sample are considerably less mobile than the women themselves. We observe 374 cross-state moves across the women in our PSID sample, compared to only 89 moves for their parents. Moreover, the grandparent moves appear to be less family-driven than the movements of the younger generation: we detect 107 moves to the parent location among the women in our PSID sample, but only 18 moves by the parents that are made to the location of their children. A potential explanation for this is that the fertility profiles in

The PSID also provides information on the year of birth of the first child of all respondents, as well as the birth years of their four youngest children. We use these years to code fertility events for our sample. If a child is born to a woman in year t, it is assumed that the woman was aware of the impending birth in year $t-1$ — in other words, $f = 1$ in year $t-1$. We limit our sample to women who are coded as either household heads or the spouses of household heads — thus, information about marital transitions and spousal earnings can be easily obtained from household head information for women labeled as spouses.

We categorize the educational attainment of our sample based on their college status at their oldest age of observation.For 75% of our sample, college attainment at age 22 was the same as college attainment at their oldest age. To account for delayed graduation, we exclude college graduates age younger than 25 when evaluating the likelihood function. Locations are based on move histories across surveys. If a respondent is observed to be living in a different state since their last interview but does not report the year in which they moved, we assume they moved in the same year as their previous interview. Earnings in the data are deflated to real 2012 dollars using the PCE deflator. To constrain the measurement error for wages in the data to reasonable levels, we winsorize hourly wages at the bottom at \$7.25 per hour and at the top at the 95th percentile. Observations that report positive hours and zero income are dropped. Observations that reported working 30 hours per week or more are coded as full-time workers, while individuals coded as working less than 30 hours per week are coded as non-participants. Individuals that report working more than 5,820 hours in a year are dropped. Finally, we limit our sample to individuals who are observed continuously in the data for at least 4 years.

B.3 Likelihood Function

The loglikelihood function used for estimation is given as :

$$L = \prod_{i}^{N} \sum_{\tau} \mathbf{Pr}(\tau) \prod_{t=1}^{T_i} \mathbf{Pr}(f = f_{it}|\Omega_{it}, \ell_{it}) \cdot \mathbf{Pr}(h = h_{it}|\Omega_{it}, \ell_{it}, f_{it}) \cdot$$
$$\mathbf{Pr}(w = w_{it}|\Omega_{it}, \ell_{it}, f_{it}, h_{it}) \cdot \mathbf{Pr}(l' = l'_{it}|\Omega_{it}, \ell_{it}, f_{it}, h_{it}).$$

For any given element in the state space (Ω_{it}, ℓ_{it}), a reservation value for the fertility

our sample often mean that women with children are likely to still have parents (especially fathers) who are strongly attached to the labor force and less mobile as a result. Our results are also unlikely to be sensitive to the gender of the PSID respondent, since maternal and paternal grandparents are located in the same location the large majority of the time.

shock $\varepsilon_f^{**}(\Omega_{it}, \ell_{it})$ can be found that governs whether a woman conceives in the given period that is given by:

$$\varepsilon_f^{**}(\Omega_{it}, \ell_{it} = \mathbb{E}_{\varepsilon_w}[V^2(\Omega, \ell; 0)] - \mathbb{E}_{\varepsilon_w}[V^2(\Omega, \ell; 1)] - (\theta_1 + \theta_2 a + \theta_3 m + \theta_4 am + \theta_5 e).$$

Likewise, for any given element in the state space $(\Omega_{it}, \ell_{it}, f_{it})$, a reservation value of the transient component of the wage offer $\varepsilon_w^{**}(\Omega_{it}, \ell_{it}, f_{it})$ can be found that governs whether the woman supplies labor in the period. Recall further that wages are measured with error:

$$\log(w) = \beta_0 + \boldsymbol{\beta X} + \eta^\ell + \varepsilon_w + \xi;$$

with $\varepsilon_w \sim N(0, \sigma_w^2)$ and $\xi \sim N(0, \sigma_\xi^2)$ distributed both i.i.d. and independently from one another. With this assumption, following Eckstein and Wolpin [1989] the first two components of the likelihood function corresponding to labor supply decisions and wages can be defined as

$$\begin{aligned} L \;=\; & \prod_i^N \sum_\tau \mathbf{Pr}(\tau) \prod_{t=1}^{T_i} \left[\Phi\left(\frac{\varepsilon_f^{**}(\Omega_{it}, \ell_{it})}{\sigma_f} \right) \right]^{1-f_{it}} \cdot \left[\Phi\left(1 - \frac{\varepsilon_f^{**}(\Omega_{it}, \ell_{it})}{\sigma_f} \right) \right]^{f_{it}} \\ & \left[\Phi\left(\frac{\varepsilon_w^{**}(\Omega_{it}, \ell_{it}, f_{it})}{\sigma_w} \right) \right]^{1-h_{it}} \cdot \left[\left(1 - \Phi\left(\frac{\varepsilon_w^{**}(\Omega_{it}, \ell_{it}, f_{it}) - \rho \frac{\sigma_w}{\sigma_\nu} \nu_{it}}{\sigma_w \sqrt{1-\rho^2}} \right) \right) \frac{1}{\sigma_\nu} \phi\left(\frac{\nu_{it}}{\sigma_\nu} \right) \right]^{h_{it}} \cdot \\ & \mathbf{Pr}(l' = l'_{it} | \Omega_{it}, \ell_{it}, f_{it}, h_{it}), \end{aligned}$$

where ϕ and Φ are the standard normal density and cumulative, respectively, $\nu_{it} = \varepsilon_{w,it} + \xi_{it}$, $\rho = \sigma_w / \sigma_\nu$, and $\sigma_\nu = \sqrt{\sigma_w^2 + \sigma_\xi^2}$, leading to $1 - \rho^2$ having the interpretation of the fraction of the wage variance attributable to measurement error. The third component of the likelihood function $\mathbf{Pr}(l' = l'_{it} | \Omega_{it}, \ell_{it}, f_{it}, h_{it})$ can be derived easily following the assumption that the location shocks $\zeta_{\ell'}$ are distributed type-1 extreme value. Denote $\bar{V}^3(\Omega, \ell, f, h, \ell')$ as the expected utility gained from selecting location ℓ' following fertility decision f and labor supply decision h after starting in state (Ω, ℓ), so:

$$\bar{V}^3(\Omega, \ell, f, h, \ell') = \beta \sum_\Omega \mathbb{E}_{\varepsilon_f}[V^1(\Omega', \ell')] \mathbf{Pr}(\Omega' | \Omega, h, f, \ell') - \Delta \mathbb{1}\{\ell' \neq \ell\}.$$

Recall that $\mathbb{E}_{\varepsilon_f}[V^1(\Omega', \ell')]$ represents the expected utility derived from optimizing over the fertility decision given ε_f, which will subsequently depend on the expected utility enjoyed from optimizing over the labor supply decision given ε_w. The method for deriving closed-form expressions of these values is presented in Appendix B.1, but their recursive nature renders it infeasible to write them out fully. With this, we can now derive the following final representation of the likelihood:

$$\begin{aligned}
L \;=\; & \prod_{i}^{N} \sum_{\tau} \mathbf{Pr}(\tau) \prod_{t=1}^{T_i} \left[\Phi\left(\frac{\varepsilon_f^{**}(\Omega_{it}, \ell_{it})}{\sigma_f} \right) \right]^{1-f_{it}} \cdot \left[\Phi\left(1 - \frac{\varepsilon_f^{**}(\Omega_{it}, \ell_{it})}{\sigma_f} \right) \right]^{f_{it}} \\
& \left[\Phi\left(\frac{\varepsilon_w^{**}(\Omega_{it}, \ell_{it}, f_{it})}{\sigma_w} \right) \right]^{1-h_{it}} \cdot \left[\left(1 - \Phi\left(\frac{\varepsilon_w^{**}(\Omega_{it}, \ell_{it}, f_{it}) - \rho \frac{\sigma_w}{\sigma_\nu} \nu_{it}}{\sigma_w \sqrt{1-\rho^2}} \right) \right) \frac{1}{\sigma_\nu} \phi\left(\frac{\nu_{it}}{\sigma_\nu} \right) \right]^{h_{it}} \cdot \\
& \frac{\exp(\bar{V}^3(\Omega_{it}, \ell_{it}, f_{it}, h_{it}, \ell'_{it}))}{\sum_{l'} \exp(\bar{V}^3(\Omega_{it}, \ell_{it}, f_{it}, h_{it}, \ell'))}.
\end{aligned}$$