Self-Employment, Workplace Flexibility, and Maternal Labor Supply: A Life-Cycle Model

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Abstract

This paper quantifies the value of self-employment as a flexible work alternative for mothers with young children and estimates how the additional flexibility affects women's long-term employment and fertility. On average, self-employed women have more control over their work schedule, hours and location than wage and salary employed women. I incorporate self-employment into a life-cycle model of married women's fertility and employment decisions and use data from the NLSY79 to estimate the value of self-employment flexibility for mothers. I find that mothers with preschool-aged children value the package of flexible amenities in self-employment at $7,000 annually, which represents around 20% of their average wage and salary earnings. A partial equilibrium counterfactual exercise suggests that self-employment flexibility encourages married women to continue working when they have young children, raising women's median lifetime earnings by 2.5%. Overall, my findings offer evidence that inflexible work causes mothers to leave the labor force in response to the high costs of managing work and family.

JEL: J13, J16, J22, and J24
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1 Introduction

American mothers have substantially increased their labor force participation, but nearly a third of women still reduce their work hours or stop working altogether after having their first child.[1] This decline in employment may harm women's future earning potential (Bertrand et al. (2010), Waldfogel (1998)). The fraction of women who are self-employed, however, does not decrease following the birth of a child.[2] These distinct employment patterns suggest that, for some mothers, self-employment is more compatible with the demands of caring for young children than wage and salary employment. Previous research suggests that self-employment provides greater flexibility in terms of work hours, schedule, and location (Devine (2001), Gurley-Calvez et al. (2009)). This flexibility may allow the self-employed to balance their work and family responsibilities and avoid a potentially costly gap in employment.

In this paper, I develop a life-cycle model of married women's fertility and labor supply to estimate the value of workplace flexibility in self-employment and to study the long-term effects of self-employment experience on earnings. In the model, having children can increase the costs of working, and this increase may vary between self-employment and wage and salary employment. The difference in the costs of working associated with children between the two types of employment captures the relative value of flexibility in self-employment. In addition to estimating how mothers value self-employment flexibility, this paper examines the long-term effects of this flexibility on earnings and employment. By studying women's self-employment experience within the broader career context, I am able to examine transitions between employment types and the returns to self-employment experience. This expands on the previous self-employment literature, which considers self-employment as a fixed characteristic (e.g. Devine (1994), Wellington (2006)). Estimating the returns to self-employment experience over a woman's career also provides more insight into its effect on the gender earnings gap, which increases with age (Goldin (2014)).

This is the first paper to include self-employment as a choice in a life-cycle model of women's decisions. A number of papers study the interaction between fertility and labor supply decisions ((Hotz and Miller (1998), Francesconi (2002), Adda et al. (2011), Keane and Wolpin (2010)), but they do not distinguish self-employment from wage and salary employment. Separating the two employment types allows me to estimate differences in their returns to experience and costs of working.

By developing a dynamic model of women's decisions, I address several difficulties in the existing self-employment literature. First, the model allows for unobserved heterogeneity in earning ability and preferences for children to account for selection into self-employment

[1] Laughlin (2011)

[2] See Lim (2015) for evidence on female self-employment and fertility.

based on unobserved characteristics. Second, it can account for the forward-looking nature of employment and fertility decisions and exploit revealed preferences to uncover the value of self-employment flexibility. Finally, by examining the workplace flexibility of self-employment, my paper adds to the compensating differentials literature and builds on papers estimating the non-pecuniary benefits of self-employment.[3]

My estimates suggest that, while wage and salary experience has the highest return for future lifetime earnings, time spent in self-employment is much better for future earnings than time spent not working. Estimates of women's utility functions reveal that the net utility cost of working is higher in self-employment than in wage and salary employment. This may reflect the stress and risk involved with being self-employed as well as a potential loss of fringe benefits. It may also explain why self-employment rates are low even though 55% of US workers state a preference for self-employment (The Gallup Organization (2010)). I find that mothers with young children face additional utility costs of working in either type of employment. However, this additional cost is about $7,000 larger for wage and salary employment. I interpret this difference as the value of self-employment flexibility for mothers. It represents around 20% of average wage and salary earnings, which suggests that mothers value workplace flexibility highly.

I use the estimates of my model to perform three partial equilibrium counterfactual exercises. First, I simulate a version of the model where self-employment is as inflexible for mothers as wage and salary employment to estimate the effect of self-employment flexibility. My simulations imply that self-employment flexibility raises women's fertility by 2.6% by lowering the costs of working while they have young children. I find that women's median lifetime earnings are 2.5% higher with flexible self-employment because it raises their lifetime work experience. In a second counterfactual exercise, I consider the effect of increasing flexibility for mothers in wage and salary employment to equal the flexibility provided in self-employment.[4] I find that increasing wage and salary flexibility raises women's fertility, increases their overall work experience, and increases their median lifetime earnings by 7.6%. My third counterfactual models the effect of policies to promote female self-employment by lowering the entry costs to self-employment. I find that lowering entry costs by 10% raises self-employment rates substantially and increases women's median earnings by 1.7%.

[3]See Hurst and Pugsley (2014) and Hamilton (2000) for papers on the non-pecuniary benefits of self-employment. There is a large literature on compensating differentials including work on the impact of fatality risk (e.g. Viscusi and Aldy (2003) and Dorman and Hagstrom (1998)), income risk (e.g. Hammermesh and Wolfe (1990) and Dillon (2015)), and fringe benefits (e.g. Lehrer and Pereira (2007)) on compensation.

[4]This exercise does not include a wage adjustment to compensate firms for the costs of implementing flexible work policies for mothers, and therefore the estimates likely overstate the effect of these policies. The counterfactual makes wage and salary employment as flexible for mothers as self-employment, however, some flexible work policies could make wage and salary employment more flexible. If firms broadly implement these policies, there could be additional benefits to women without young children.

Although it makes the flexible work alternative less costly, I find that reducing the entry costs to self-employment has basically no effect on fertility.

While all three counterfactuals suggest that increased access to flexible work raises women's lifetime earnings, only increasing the flexibility of wage and salary employment diminishes the overall gender earnings gap. In general, increasing flexibility for mothers raises women's lifetime work experience and earnings by encouraging them to work while they have young children. However, the women who are encouraged to work tend to be lower-earning, which decreases the average earnings among employed women. In my counterfactual exercise with increased wage and salary flexibility, I find that the effect of additional work experience outweighs the selection of lower-earning women into employment. Increasing the flexibility of self-employment has an additional negative impact on employed women's earnings because it encourages women to become self-employed, and self-employment earnings are 30% lower than wage and salary earnings. I estimate that self-employment flexibility exacerbates the gender earnings gap among younger workers and reduces it among older workers, resulting in little overall effect on the gender earnings gap. Nevertheless, the flexibility of self-employment makes women better off. This highlights the importance of considering non-pecuniary benefits and labor force participation in addition to the earnings of employed women.

My results offer additional evidence that workplace flexibility decreases employment gaps during the childbearing years, complementing previous work by Goldin (2014), Herr and Wolfram (2012), and others. This paper takes a different approach by using self-employment to study workplace flexibility, but reaches the same conclusion: a lack of workplace flexibility causes some mothers to leave the labor force. Many of the aspects of self-employment flexibility can be seen in the existing policies of some firms. Policies like flextime mimic the ability to change working hours on a day-to-day basis, while telecommuting allows employees to work from home. My model provides a monetary estimate for the value of the flexibility offered by self-employment, which can be compared to firms' costs when evaluating whether to implement these policies. While these results show that self-employment is one way that mothers gain flexibility, I also estimate substantial costs associated with self-employment. This suggests that self-employment is not for everyone and highlights the need for more flexible work alternatives within wage and salary employment.

The remainder of the paper is structured as follows. Section 2 provides some background on female self-employment. Section 3 describes the model of fertility and labor supply and discusses identification of the model parameters. Section 4 describes the data I use to estimate the model. In section 5, I discuss the parameter estimates from the model, with a particular focus on women's earnings and utility parameters. Section 6 describes the results

from the three counterfactual exercises and section 7 concludes.

2 Background: Self-Employment and Flexibility

2.1 Female Self-Employment and Children

Previous research has found that women with young children are more likely to be self-employed. A number of papers have shown that women's self-employment is positively associated with both marriage and children (Devine (2001), Lombard (2001), Wellington (2006)). In other work, I have studied how self-employment behavior changes with the age of a woman's youngest child (Lim (2015)). I find that the presence of a child between the ages of one and six has a positive effect on a woman's self-employment propensity that is both substantively and statistically significant. This association follows an inverted U-shape with respect to the age of a woman's youngest child; the effect is strongest when the youngest child is two years of age. The positive relationship between self-employment and young children is not conditional on employment.[5] The shape of this relationship is consistent with the hypothesis that self-employment provides a means to work while caring for children during the years when they require the most attention.

Because the empirical evidence suggests that the decision to be self-employed and the decision to have children are interrelated, I model them as a joint decision. My model allows the presence of children to affect the decision to become self-employed and for the option of self-employment to influence fertility.

2.2 Workplace Flexibility and Female Self-Employment

Researchers have focused on workplace flexibility as a primary explanation for the positive relationship between female self-employment and children. They have identified the following main factors to explain why mothers with young children are more likely to choose self-employment: the ability to work from home, the ability to work fewer hours, and control over work load and schedule. Around 25% of self-employed mothers with young children work from home compared to only 5% of wage and salary employed mothers (Lim (2015)). Time use analyses find that self-employed mothers spend more time with their children, work fewer hours, and spend more time on housework (Gurley-Calvez et al. (2009), Hundley (2000), Lim (2015)). Additionally, the distribution of hours worked in a day varies much

[5]This relationship would be even stronger if conditioned on employment because wage and salary employment rates decline when women have young children. Then the self-employment rate among employed women would be increasing even if the self-employment rate among all women were constant or even falling.

more across self-employed women suggesting that they have more control over their day-to-day and overall schedules. Using panel data, Devine (2001) finds that self-employed women vary their work hours more throughout the year, suggesting that the self-employed can make changes to their work schedules relatively often.[6] Self-employment appears to allow mothers to choose both how much and when they work. Additionally, the self-employed can often work from home, which makes it easier to spend more time with their children.

Although self-employment provides a more flexible work environment, there are many reasons why only 5% of married women are self-employed. Certain occupations lend themselves to self-employment. As Table 1 shows, the most common occupations among the self-employed are child care workers, administrative workers, managers, and sales workers.[7] The level and type of flexibility that each occupation achieves in self-employment can differ and may be less flexible in some ways than working a similar job in wage and salary employment.[8] Additionally, becoming self-employed can be financially risky and require startup capital. It can also result in the loss of fringe benefits such as employer retirement contributions and employer-sponsored health insurance.

Although only a small fraction of women are self-employed at any given time, nearly 30% of women are self-employed at some point in their career.[9] Very few women, however, spend the majority of their working lives in self-employment, making the question of how self-employment experience affects future earning potential in wage and salary employment relevant.

2.3 Workplace Flexibility: Access and Impacts

Many of the features of general flexible work arrangements are incorporated in self-employment, but many workers do not have access to these types of flexibility within wage and salary employment.[10] In 2011, 56% of US wage and salary employees had the ability to vary their schedule or the location of their work (Council of Economic Advisors (2014)). Although the majority of employers offer flexible work policies for some employees, relatively few offer the programs to all or most of their employees (Matos and Galinsky (2014)). Individual-level

[6]There is little evidence that changes in hours in self-employment is due to slack demand. Devine (2001) finds that temporary part-time work among the self-employed is involuntary only 3% of the time compared to 10% of the time for wage and salary employed women.

[7]These tabulations are for my sample of NLSY79 married, white women. For a more comprehensive look at the top occupations among all self-employed American women over time see Table A2.

[8]For example, Goldin and Katz (2012) argue that pharmacists represent an occupation that is less flexible in self-employment.

[9]Author's tabulations from NLSY79 data.

[10]See `www.workplaceflexibility2010.org` at Georgetown Law for details on a variety of flexible work policies.

data suggest that workers with a Bachelor's degree are more likely to have access to flexibility in their schedules and place of work than less educated employees (Golden (2001), Council of Economic Advisors (2014)). Overall, the evidence suggests that many workers do not have a flexible work environment.

There is some research suggesting that workplace flexibility is important in determining mothers' employment decisions. Much of the work has focused on the effect of maternity leave. Paid leave seems to be more effective than unpaid leave to encourage employment among mothers. Both Rossin-Slater et al. (2013) and Byker (2014) find that paid leave in California raised women's employment, while Han et al. (2009) find no relationship between employment and the short and unpaid maternity leave provided by the 1993 Family and Medical Leave Act. Other papers have focused on measuring the flexibility within an occupation and estimating its impact on women's choices. Herr and Wolfram (2012) find that among Harvard graduates, women in flexible jobs are 5-6 percentage points less likely to stop working after having children. Goldin (2014) provides some evidence that the most flexible occupations have the smallest gender earnings gaps. This paper estimates the effect of the package of flexible amenities self-employment provides on women's short and long-term employment decisions.

3 Model

In this section, I describe my model of the employment and fertility decisions of married white women over their working lives. I study married women for two reasons. Empirically, the effect of young children on self-employment rates is largest for this group, making it a relevant population to study (Lim (2015)). Additionally, self-employment rates among married women are around 9% compared to 3% for never married women (Roche (2014)). Second, I do not model household bargaining over child care and home production, which makes the model ill-suited to estimate the different considerations single and married women face in making employment and fertility decisions. I limit my analysis to white women in order to reduce the number of estimated parameters by focusing on a relatively homogenous sample.[11] Additionally this sample selection allows me to compare my results to previous work on married white women.[12]

Figure 1 depicts the overall timeline of the model. The model begins at age A_0, which is individual specific and is defined as the first year when all three of the following events

[11]Black and Hispanic women have different self-employment rates, may face different earnings processes or have differing preferences over children and work, which would require estimating separate parameters by race. In the data, I do not have the sample size to run a separate model for Blacks and Hispanics.

[12]For example Francesconi (2002) and Eckstein and Wolpin (1989).

have occurred: the woman is at least 18 years of age, she is married, and she has been out of school for at least two years. The estimation begins after almost all schooling has been completed because I am not modeling education decisions.[13] Similarly the estimation begins after women marry because the model abstracts from the marriage decision and does not allow for divorce.[14] In each year between ages A_0 and 50, women decide between wage and salary employment, self-employment, or non-employment. If the woman has fewer than four children and is under the age of 40, she also chooses whether to have a child that year.[15] In years when women make both an employment decision and a fertility decision they choose from six alternatives, and in years with only an employment decision they choose from three. Between the ages of 51 and 65, I assume women no longer make a forward looking employment decision, but rather solve a static utility optimization over the employment choice each year given the value of their state at age 50. Their utility each year is determined by their previous employment and fertility decisions. At age 65, women retire and the model ends.[16]

The model incorporates two dynamic considerations: human capital accumulation through work experience and children. When women decide whether to be employed, they consider the effect of the decision on their future earning potential. Likewise, when women have children they fully anticipate the need to care for the child and the benefits of having children. In the remainder of this section, I discuss the empirical specification of the model, describe the estimation procedure, and discuss the identification of key parameters.

3.1 Utility Function

Women make decisions to maximize the present value of their expected utility:

$$E_t\big[\sum_{\tau=t}^{65}\delta^{\tau-t}U(c_\tau, d_\tau^j, N_\tau, a_\tau, \epsilon_\tau^{jn})\big] \tag{1}$$

where δ is the discount factor, c_τ is the woman's consumption in year τ, d_τ^j is a vector of indicators for the employment choice where $j \in \{ws, se, ne\}$ for wage and salary, self-

[13] In the data, I consider the beginning of the first two consecutive years out of school as the beginning of the eligible sample period. Women remain in the sample even if they return to school later.

[14] In the data, I focus on women in long-term marriages. Incorporating the decision to divorce greatly complicates the model, and I leave this extension to future work.

[15] This maximum was set to ease computation. Around 3.5% of women in my sample have more than 4 children. I assume perfect control over fertility, but unexpected pregnancies will be justified in the model by a large positive fertility shock.

[16] Women may receive utility in retirement but it must be unrelated to any state variables in the model such as number of children, work experience, and demographics. This implies that earlier employment and fertility decisions are not motivated by a desire for grandkids or large retirement savings. These considerations are beyond the scope of my model.

employment, and not employed respectively. N_τ is the total number of children a woman has (including a child born in period τ), n is an indicator for a birth, and a_τ is the age of the woman's youngest child. In each year, women receive utility from consumption, their children, and leisure. Leisure is not explicitly modeled, but the loss of leisure from working is reflected in the cost of employment. Women's period-specific utility is specified as follows:

$$U_t = \begin{cases} \beta_1^j c_t + \beta_2^j + \beta_3^j \mathbb{1}(a_t \in [0,5]) + \beta_4^j \mathbb{1}(a_t \in [6,9]) + \beta_5^{se} \mathbb{1}(D_t^{se} = 0) & \\ \qquad +\beta_6 N_t + \beta_7 (N_t)^2 + \epsilon_t^{jn} & \text{if j} \in \{ws, se\} \\ \\ c_t + \beta_6 N_t + \beta_7 (N_t)^2 + \epsilon_t^{jn} & \text{if } j = ne \end{cases} \tag{2}$$

The first part of the equation describes women's utility if they work and the second describes their utility when they are not employed. Parameters and variables with j superscripts vary by the employment choice, while those with n superscripts vary with the fertility decision. The vector D_t^j represents the stock of type j employment experience.

The marginal utility of consumption, β_1^j, can differ by employment status, which allows for husband's earnings to affect women's decisions.[17] An estimate of β_1^j that is less than 1 suggests that, all else equal, women with wealthier husbands are less likely to work in that employment choice. An estimate greater than 1 implies that women with high earning spouses are more likely to work in that employment choice.

The utility costs of working may vary by employment type and the presence of young children. The net utility costs of working in either self-employment or wage and salary employment are given by β_2^j. These costs are modified by the presence of young children through β_3^j and β_4^j. Specifically, β_3^j describes the additional psychic costs of working when a woman's youngest child is between the ages of 0 and 5. Similarly, β_4^j represents the additional utility cost of working associated with having a youngest child aged 6 to 9. I allow for different effects for preschool-aged children and older children because schools may provide care that makes it easier for women to work.[18] I interpret the difference between β_3 and β_4 in self-employment versus wage and salary employment as the value of self-employment additional value of flexibility for mothers with young children. The overall benefit of self-employment flexibility that all workers enjoy will be captured in the β_2 term. This particular specification

[17] My model only includes the wife's employment decision, and I model the husband's earnings as an exogenous process. I assume a unitary household model, where income is pooled and not bargained over. This simplifies the analysis, but it implies that the model does not incorporate considerations such as bargaining power in determining women's employment decisions.

[18] My model includes estimates of expected child care costs, which will reflect the lower monetary costs of child care as children age. The disutility parameters β_3 and β_4 should be interpreted as non-pecuniary costs of working with children such as less time spent with children.

assumes that women with no children and women with a youngest child 10 years of age or older face the same utility costs of working. This specification is motivated by my previous work showing that employment rates among mothers with children older than 10 are similar to those without children. It also reduces the computational requirements of the model because I only follow the youngest child through age 9.[19] Finally, β_5^{se} represents a fixed cost paid the first time a woman becomes self-employed. This cost represents any extra effort spent moving into self-employment for the first time including time spent learning about how to start a business and time spent securing financing and proper licensing for the business.[20]

I allow the number of children a woman has to affect her utility directly. I assume that children arrive in the same year that women decide to have a child. The utility from children is modeled as a quadratic in the number of children. Women receive this utility from children regardless of their employment choice.

For each of the six possible choices in each year, there is a choice-specific random utility shock, ϵ_t^{nt}. These shocks are assumed to be serially uncorrelated, and independent and identically distributed according to a type 1 extreme value distribution with variance $\rho^2 \frac{\pi^2}{6}$ where ρ is an estimated parameter. This error structure greatly reduces the computational burden associated with estimating the model, but has a number of strong implications. First, the variance of the shocks to self-employment and wage and salary employment are equal, ruling out different second moments for the earnings in each employment type.[21] Second, the shock to utility in each employment type with a birth is uncorrelated with the shock to utility in that same employment type with no birth. Likewise the shocks to utility across the employment types with a birth are uncorrelated. Third, this specification rules out persistent shocks by assuming that the errors are uncorrelated over time.

3.2 Budget Constraint

The budget constraint determines women's consumption levels each year. Consumption is equal to the sum of the woman's earnings, m_t^j, and her husband's expected income, y_t, less

[19] See Lim (2015) for patterns of employment and self-employment as a function of the age of a woman's youngest child. As explained in the estimation section, for computational reasons I only keep track of the youngest child's age through 9.

[20] This specification does not include a switching cost for moving in and out of self-employment. These costs might be minimal if the woman re-starts a business in a similar occupation or large if the woman moves into a different occupation. I don't model occupational choice so I chose to have a one time fixed cost of becoming self-employed for the first time.

[21] Although ϵ is a utility shock, a transformation of the shock could instead be added to wages and interpreted as a wage shock.

the family's predicted child care costs, CC_t^j:

$$c_t^j = m_t^j + y_t - CC_t^j \tag{3}$$

There is no saving or borrowing in the model, so women consume their full net income each year.[22]

I assume that the husband's expected earnings, y_t, are exogenous to their decisions, but they are modeled as a function of the wife's characteristics (Francesconi (2002), Van der Klaauw (1996)). I assume that the husband's earnings in each year are realized after the wife makes her employment and fertility decisions, so women make decisions based on the expected earnings of their husbands. The husband's log income is modeled as a function of the wife's education level, her age, and the interaction between the two. This allows for his earnings to grow over time at a different rate depending on the wife's education level. I also control for the unemployment rate and an individual level fixed effect, which captures fixed characteristics that determine husbands' average lifetime earning levels. These characteristics could include their education level, college major, or unobserved ability.

Women's earnings when employed depend on their previous experience in each type of employment, D_t^{ws} and D_t^{se}, and the cumulative number of years spent not employed, D_t^{ne}. Earnings also depend on the national unemployment rate, u_t, and the woman's education level, $\boldsymbol{X}$, both of which are assumed to be exogenously determined outside of the model. I assume that women have no earnings if they choose not to work: $m_t^{ne} = 0$. Log annual earnings in each employment type are specified by the following earnings equation:

$$\ln(m_t^j) = \gamma_0^j + \gamma_1^j u_t + f^j(D_t^1, D_t^2, D_t^3) + \boldsymbol{\gamma^j X} + \xi_t^j;\ j = ws, se \tag{4}$$

The functions f^j are piece-wise linear functions that captures how log earnings in each employment type vary with years of experience and years spent not employed. The functions include a top experience category after which additional years of experience no longer contribute to changes in earnings. I model log earnings this way because it provides a better fit to the data than a quadratic function. Additionally, a quadratic function was problematic for predicting earnings at high levels of self-employment experience because it required extrapolation outside the empirical support of the experience distribution. This specification flexibly allows the returns to each type of employment experience to vary between wage and salary employment and self-employment.

[22]This assumption is made for tractability reasons and is common in the literature (see Van der Klaauw (1996), Francesconi (2002), Keane and Wolpin (2010)). A savings decision represents a continuous choice that would greatly increase the computational burden of solving the model. With linear utility and no savings the problem is equivalent to a lifetime wealth maximization problem.

There are many reasons that the returns to experience might differ across employment types. The skills learned in self-employment might be particularly beneficial to running a business, which is likely to involve a variety of types of tasks but might be less useful in wage and salary employment when the assigned tasks are more specialized. Employers may find valuing self-employment experience difficult because it might be hard to verify. By including time spent not employed in the earnings equation, I allow for an earnings penalty for time spent not employed. Previous research suggests that both the length of time spent not-employed as well as how recent the time out was matter (e.g. Jacobsen and Levin (1995), Hotchkiss and Pitts (2007)). While this specification does not control for the timing of the employment gap, it will control for the average penalty to earnings over many years associated with an employment gap.[23]

In order to accurately model mothers' employment decisions, I explicitly estimate expected child care costs. Previous research has found that the labor supply of married women is sensitive to the cost of child care (Ribar (1992), Connelly and Kimmel (2003), Heeb and Kilburn (2004), Haeck et al. (2015)). Ideally, I would model women's child care decision using data on child care options and prices. Unfortunately these data do not exist, so I use data on women's child care expenditures to estimate their expected child care costs under each employment and fertility decision.

I predict women's child care expenditures as a function of the mother's characteristics, the age of her youngest child, the number of children in her family, and her employment type. The expected child care expenditure is the product of the probability that a working married mother pays a positive amount for child care and the expected amount paid conditional on positive payment.[24] Around 55% of working mothers with children under 10 do not make a monetary payment for child care services, so zero payments are empirically important for estimating the expected child care cost. The probability of a positive payment is described by the following equation:

$$\begin{aligned} Pr(Payment_t^j) = &\sum_{l=1}^{3+} \nu_l \mathbb{1}(N_t = l) + \nu_4 \mathbb{1}(d_t^{se}) + \nu_5 \mathbb{1}(a_t \in \{0,1\}) \\ &+ \nu_6 \mathbb{1}(a_t \in [2,5]) + \nu_7 year_t + \boldsymbol{\nu} \boldsymbol{X_t};\ j = ws, se \end{aligned} \tag{5}$$

[23]Keeping track of the timing of experience would vastly increase the state space making the model computationally intractible.

[24]This is a reduced form model to predict the monetary costs that women can expect to pay in each employment type. If women who do not work are systematically different on unobserved dimensions that influence their cost of child care, this procedure may overestimate or underestimate their expected child care costs. For example, suppose women who do not work tend to not live nearby a grandparent and therefore would have a higher probability of having to pay for child care costs than those who do work. Child care costs would be underestimated for these women, and the disutility of work would be overestimated.

The expected amount paid conditional on positive payment takes the exact same functional form:

$$E(Cost_t^j|Payment_t^j) = \sum_{l=1}^{3+} \phi_l \mathbb{1}(N_t = l) + \phi_4 \mathbb{1}(d_t^{se}) + \phi_5 \mathbb{1}(a_t \in \{0,1\}) + \phi_6 \mathbb{1}(a_t \in [2,5]) + \phi_7 year_t + \boldsymbol{\phi X_t};\ j = ws, se \tag{6}$$

Then the expected child care cost is:

$$CC_t^j = Pr(Payment_t^j) * E(Cost_t^j|Payment_t^j);\ j = ws, se \tag{7}$$

This specification takes into account that most daycares charge more for infants than preschool or school-age children. It also implicitly allows for differences in the number of hours of care purchased for school-age children relative to preschoolers. I assume that there are no child care costs for women whose youngest child is 10 or older and for those who are not employed.[25] The vector of individual level characteristics, $\boldsymbol{X_t}$, includes education level and a quadratic in the mother's age. This accounts for differences across education levels and age in the decision to use child care and the type of care selected. A linear time trend is included to pick up changes over time in real child care prices.[26]

I allow child care costs to differ for self-employed mothers because my previous research suggests that they are more likely to work from home and spend more time supervising their children (Lim (2015)). They also may have an easier time rearranging their work schedules allowing them to coordinate child care with their husbands. By allowing child care costs to be lower for self-employed women, I am in some sense controlling for some of the benefits of self-employment flexibility. I will interpret my results on self-employment flexibility as net of child care expenses because these costs are already taken out of women's consumption. Controlling for lower child care costs among the self-employed biases me against finding additional flexibility within self-employment so I choose to explicitly account for lower child care costs and discuss them as an additional benefit of self-employment for mothers.

[25] In the Survey of Income and Program Participation child care data, around 5.6% of working married mothers with a youngest child 10-14 have positive child care expenditures and the unconditional average expenditure is only $2 per week.

[26] The time trend will pick up average changes in prices arising both from changes in the underlying costs of providing the same quality care as well as changes in the average quality of care utilized. See Laughlin (2011) for trends in child care costs over time.

3.3 Unobserved Types

Women may vary in their preferences and their earning abilities due to factors that are unobserved to the researcher. In order to allow for unobserved traits to affect women's choices, I allow for three latent types of women indexed by k.[27] The types are represented as discrete mass points as in Heckman and Singer (1984) and the proportions of each type, μ_k are estimated parameters. These latent types are unknown to the researcher but are known to each woman. I allow women's preferences for children to reflect underlying differences across the population in the desire to have children. This modifies the utility equation, (2), by allowing the parameters on the utility of children to vary by type: β_6^k and β_7^k. I also allow women to vary in their abilities in both wage and salary employment and self-employment to account for selection on unobserved traits in the earnings equations. The women's earning equation, (4), is modified to have an intercept term that can vary by type: γ_0^{jk}.

3.4 State Space Evolution

Women's decisions depend on their previous fertility and employment choices, the values of the exogenous variables that affect utility, and the realizations of their choice specific utility shocks. The relevant state space that determines their optimal choice includes $y_t, CC_t^j, \boldsymbol{X_t}, k, N_t, D_t^{ws}, D_t^{se}, D_t^{ne}, u_t, a_t, \epsilon_t^{jn}$, which I denote as Ω_t. Women have full information regarding the models determining husband's income, child care expenditures, their own earnings, and their utility. The only remaining uncertainty in the model are the choice specific utility shocks. The years of employment experience, the number of children, and the age of the youngest child all evolve deterministically according to women's choices in the model. Work experience and children born prior to the estimation period are included in women's state values.

The parameters of the model are represented in the vector θ. $V_t(\Omega_t, \theta)$ represents the present value of a woman's expected utility in year t given Ω_t and θ:

$$V_t(\Omega_t, \theta) = \begin{cases} \max\limits_{j,n} \left[V_t^{jn}(\Omega_t, \theta)\right], & \text{if } t \in [A_0, 40] \text{ and } N_t < 4 \\ \max\limits_{j} \left[V_t^{j0}(\Omega_t, \theta)\right], & \text{if } t \in [41, 50] \text{ or } N_t = 4 \end{cases}$$

In years through age 40 when women have fewer than 4 children they make a fertility and employment decision. Between the ages of 41 and 50 and for years when they have 4 children, women only make an employment decision. Between the ages of 51 and 65, women conduct a static optimization problem and select the best employment choice each year conditional

[27] Allowing for three types fit the data well and were tractible to estimate.

on their state at $t = 50$ and the observed utility shocks in that year. $\bar{V}_t^{jn}$ represents the alternative specific value functions for each of the possible choices, which can be represented as a Bellman equation:

$$\begin{aligned} \text{For } t \in [A_0, 50]: \quad & \bar{V}_t^{jn}(\Omega_t, \theta) = U_t(d_t^j, n_t, \Omega_t, \theta) + \delta E(V_{t+1}(\Omega_{t+1}, \theta)|\Omega_t, d_t^j, n_t) \\ & \text{where } n_t = 0 \text{ for } t \in [40, 50] \text{ or } N_t = 4 \\ & \text{and } E(V_{51}(\Omega_{51}, \theta)) = E \sum_{t=51}^{65} \delta^{t-51} \max_j \left[U_t(d_t^j, \Omega_t, \theta|\Omega_{50})\right] \end{aligned} \tag{8}$$

3.5 Identification

In my model, the parameters are identified by the choice and earnings data combined with the functional form assumptions, the distributional assumptions, and exclusion restrictions. Although the parameters are jointly determined, in this section I provide an intuitive description of specific types of variation in the data that are particularly relevant to identify certain parameters. Table A1 summarizes the parameters of the model and the identifying variation in the data.

Women's earnings parameters are primarily identified by the earnings data. The unemployment rate, women's education level, and women's cumulative work experience are exclusion restrictions that help identify the earnings parameters because they affect women's earnings but not utility directly. The parameters in the piece-wise linear functions that describe the relationship between experience and earnings are identified by earnings data observed for women with the same education level in the same year, but with different previous experience levels.

Women's utility parameters are identified by the choices women make in the data. The number of children a woman has, the age of her youngest child, and her husband's predicted income act as exclusion restrictions that affect women's utility in the different choices, but do not influence her potential earnings in employment. The overall share of women working in wage and salary employment and self-employment identify β_2^j. The difference between the observed employment choices for women with young children and those without identify the costs of working associated with children, β_3^j and β_4^j. Finally the fixed cost of entering self-employment for the first time, β_5^{se}, is identified by the fraction of women who ever become self-employed.

My main estimate of interest is the difference in the additional costs of working associated with having young children at home between wage and salary employment and self-employment, $\beta_3^{ws} - \beta_3^{se}$. This difference is identified by differential changes in the two employment rates associated with having a young child at home. For example, descriptive

analyses show that wage and salary employment rates decline sharply with the presence of young children while self-employment rates do not (Lim (2015)). These differences in behavior are identifying the difference between these parameters.

The panel nature of the data allow me to identify the fraction of individuals in each latent type and the type-specific parameters. By observing the same woman multiple times, I can estimate the unobserved constant contribution to earnings and utility separately from the unobserved idiosyncratic error term. These type specific parameters are identified by women who look similar on observed characteristics making consistently different choices or having different earnings.

3.6 Estimation

The estimation procedure consists of two stages. First, I estimate the husband's earnings equation and the child care cost equations using OLS and probit regressions. I use these predicted values in the second step to estimate the utility parameters and women's earnings equations. In the second stage, for each guess of θ, I solve the full dynamic programming problem for each individual using backward induction and construct the likelihood of the observed data. Given the distributional and independence assumptions on ϵ, the log likelihood of observing a sequence of choices and log earnings over time for a number of women, I, can be written as:

$$\ell = \sum_{i=1}^{I} \ln \left(\sum_{k=1}^{3} \prod_{t=A_0}^{T} \mu_k \frac{e^{\bar{V}_t^h(\Omega_t,\theta)/\rho}}{\sum_{h=1}^{H} e^{\bar{V}_t^h(\Omega_t,\theta)/\rho}} \left(\phi \left(\frac{\ln(\hat{m}_t) - \ln(m_t)}{\sigma} \right) \right) \right) \tag{9}$$

To reduce the computational burden of estimation, I make a number of modeling assumptions. First, I assume that the choice specific error terms, ϵ, are distributed according to a type one extreme value, which yields an analytical solution to the expectation in the Bellman equation (8). Second, I only allow women to have a maximum of four children. Third, I only keep track of the youngest child's age through age 9.[28] This allows me to differentiate between the costs of working for women with preschool versus elementary aged children, while keeping the state space relatively small. Fourth, I do not allow women to make decisions after age 50. This reduces the number of periods that I need to solve the dynamic programming problem over, while still allowing me to focus on the period of women's lives most relevant for my research questions. I am also able to speed up the search over the parameter space by providing analytical derivatives for the likelihood function.

[28] Older children still enter women's utility functions through the utility gained from having children. The assumption in the model is that the costs of employment for women with children 10 and older are the same as for women with no children.

Instead of normalizing the variance of the random utility error, I use women's earnings, husband's expected income, and child care costs to denote utility levels in dollars. All dollar values in the model are measured in real 2000$, and I estimate the variance of ϵ. I fix the discount factor, δ, to be 0.95.[29]

4 Data

In this section, I explain how I map women's employment, fertility, and earnings histories into an annual level dataset that I use to estimate my model. I also describe the data used to estimate the expected child care costs associated with working.

4.1 National Longitudinal Survey of Youth 1979 (NLSY79)

My primary data source is the NLSY79, which follows 12,686 individuals who were 14-22 years of age in 1979 through the present day. The survey interviews respondents annually from 1979 through 1993 and bi-annually starting in 1994.

My primary sample includes white women who marry and do not divorce during the survey.[30] Around 38% of married white women divorce during the survey.[31] In Table A3, I show that individuals in my sample who are always married do differ along observed characteristics from individuals who get divorced. Women who divorce marry earlier, have less education, and lower family incomes than women who remain married for the entire sample. These differences are statistically significant and economically large, and they fit with known patterns of divorce (e.g. Bramlett and Mosher (2002)). However, the differences in employment and fertility choices between the women who divorce and those who remain married are not particularly large from an economic standpoint and are mostly statistically insignificant.[32]

There are two general sources of bias caused by this sample selection. First, systematic differences in preferences for work and children between women who divorce and those who

[29] A variety of papers use similar discount factors. Francesconi (2002), Adda et al. (2011), and Keane and Wolpin (2010) fix the discount factor to something between 0.93 and 0.952. Keane and Wolpin (1997) estimates the discount factor to be 0.936.

[30] Women in my sample may get divorced after leaving the survey. I do not consider cohabiting women as married, however evidence on white men in the NLSY79 suggests that 70% of live-in relationships began as marriage and 30% as cohabitation. The majority of cohabitations led to marriage with the same partner (Oppenheimer (2003)).

[31] An alternative sample is one that includes women while they are married regardless of whether they divorce. If women change their behavior in anticipation of divorce (see Poortman (2005)), the estimates will be biased, however, the main results are similar when I include women who are ever married.

[32] See Francesconi (2002) for similar findings on these two samples. He argues ever married and always married women are similar in their employment and fertility decisions.

do not. Second, systematic differences in unobserved factors that affect earning potential, such as ability. In practice, the model estimates are similar when including all white married women in the estimation sample suggesting that women who divorce behave similarly to women who do not while they are married.

My estimation sample only includes the nationally representative sample from the NLSY79. Using this sample, makes my estimates more relevant to the white US population as a whole. I make a number of smaller refinements to the original NLSY79 sample to create the data I use to estimate my model. These are explained in detail in Appendix B and Table B1 shows how each restriction affects the sample size. The final sample includes 1,083 women and 23,839 person-year observations.

The NLSY79 includes detailed information on marriage, fertility and employment and covers the relevant age range for my life-cycle model. I use this information to construct an annual level dataset of employment and fertility choices.[33] In each year, women are categorized as self-employed, wage and salary employed or not employed according to the most common status among the weeks in that year. I consider women who were unemployed or out of the labor force to be not employed.[34] Within a year, many women have weeks assigned to different employment types highlighting the importance of interpreting the effect of self-employment as the effect of a year of being primarily self-employed. I calculate women's annual earnings as the sum of their weekly earnings from all of their jobs. There is some evidence that survey measures of self-employment income are underestimated because individuals under-report this income for tax reasons (Hurst et al. (2014)). My earnings measure does not use questions about annual income, and instead uses job specific information on pay rates and hours. This may mitigate some of the under-reporting, but any remaining systematic under-reporting would positively bias the utility cost of working in self-employment.[35] Please see Appendix B for more detail on the dataset construction.

Information about the estimation sample can be seen in Table 2. The average age at the beginning of estimation is 25 and on average there are 26 years of data for each woman. Average earnings during years when women are categorized as wage and salary employed are around 36 thousand dollars, which is much higher than the 23 thousand dollar average for years when women are self-employed. These earnings differences include differences arising both from hourly wage rates and from hours worked decisions. Around 41% of the sample

[33] If women have a birth after 40, I ignore it and assign them to their employment status with no birth. Around 2% of women in the sample have births after 40.

[34] This will affect the long-term unemployed. My model assumes that if women want to work at their predicted wage rate, which will be lower in worse economic times, they can find a job.

[35] I do find that both hourly wages and earnings are lower in self-employment. This is consistent with previous work on self-employment (Hamilton (2000)), and it is not clear what portion is from under-reporting of self-employment earnings versus real lower earnings in self-employment.

have a high school degree or less, 24% have some college, and 35% have a Bachelor's degree.

Table 3 shows the variation in the percentage of women selecting each choice by age and number of children. Around 28% of person-years are spent not-employed, 66% are spent in wage and salary employment and 6.4% in self-employment. Overall employment rates are increasing in age. Consistent with previous evidence that there is a strong positive relationship between age and self-employment, older women are more likely to be self-employed. Self-employment rates rise with the number of children in contrast to the percentage of women working in wage and salary positions. Women with many kids are also more likely not to work. Table 4 shows the year-to-year transitions between choices. There is a high level of persistence in the employment choice with nearly 90 percent of women who worked in wage and salary employment last year continuing in a wage and salary position. Self-employment and non-employment are slightly less persistent with continuation rates of closer to 80 percent.

4.2 Child Care Expenditure Data

Child care expenditure data come from the Survey of Income and Program Participation (SIPP). The SIPP is a longitudinal panel that follows individuals for up to 4 years and periodically asks questions about child care expenses. I use SIPP panels from 1984 through 2008, which have child care expenditure data for 15 different years spanning 1986-2011. See appendix Table B2 for more information on the specific panels and survey waves used. I limit the sample to white married employed mothers with a youngest child under the age of 10.[36]

5 Parameter Estimates

In this section, I discuss the parameter estimates from both the first and second stage estimation. I also provide evidence that my model fits the life-cycle patterns and overall employment and fertility choices observed in the data, which lends credibility to the conclusions from my counterfactual exercises.

5.1 First Stage Results

In the first stage of estimation, I generate predictions for expected child care costs and husband's earnings. The results from the regressions predicting positive child care payment and the conditional child care expenditure are shown in Table A4. Women with infants,

[36]Although non-working women do purchase child care, the SIPP did not record expenditures for non-employed women across all panels.

older women, and more educated women tend to pay more for child care. The self-employed are around 25 percentage points less likely to make positive payments for child care, but conditional on payment pay only slightly less per week.

In each interview, women in the NLSY79 are asked about their spouse's income, which I use to estimate a model of husband's income in the first stage of estimation. The estimates from the husband's income regression are shown in Table A5. Husband's earnings increase with the wife's age, and husbands of women with a Bachelor's degree have higher earnings and somewhat higher earnings growth.

5.2 Women's Earnings

Table 5 shows the earnings parameter estimates and Figure 2 plots the effect of experience on wage and salary and self-employment earnings. The level at each year of experience represents the change in log earnings associated with that level of experience relative to 0 years of that type of experience with all other factors held constant. The effects are additive because there are no interactions between experience types. I show the same results in table format in the bottom portion of Table 5. The values in the table represent the ratio of predicted log earnings relative to an individual with 0 years of that type of experience all else held constant.

Figure 2 clearly shows that wage and salary experience has higher returns in wage and salary employment and that self-employment experience has higher returns in self-employment. More self-employment experience is associated with higher wage and salary earnings, which contrasts sharply with the negative earnings effects of time spent not employed. These results indicate that being self-employed maintains and even increases women's future earning potential in wage and salary employment. I estimate that wage and salary experience is associated with a small negative but mostly zero effect on self-employment earnings. Because the model describes log earnings and not log wages, the parameter estimates reflect the combined effect on women's wage rates and their hours worked. This is particularly important for interpreting the coefficients in the self-employment earnings equation because self-employed women often work part-time (Devine (2001)). Women with higher levels of wage and salary experience may have higher wages within self-employment but work fewer hours. As in wage and salary earnings, I estimate a negative effect of years spent not employed on self-employment earnings.

The magnitudes of the returns to experience in wage and salary employment are in line with previous estimates. Although they use a different specification, dataset, and focus on log wages, my estimates are similar to Light and Ureta (1995). They estimate that 3, 5, and 8 years of actual experience increase white women's log wages by 0.20, 0.31, and 0.44

log points respectively. I find estimates of 0.36, 0.43, and 0.53 log points, which are higher than theirs but are closer to their preferred richer specification.[37] My estimates of the effect of years spent not employed on wage and salary earnings are also generally consistent with previous research. Jacobsen and Levin (1995) focus on the rebound in earnings after an employment gap and find that the log wage penalty varies from -0.30 log points 1 year after the gap to around -0.05 log points 20 years after the gap. I estimate that a 1 year gap leads to a 0.09 log point decline in wage and salary earnings, which seems reasonable because the estimate is the average penalty to earnings in all future years.[38]

As Table 5 shows, more educated women earn more in wage and salary employment, but the pattern is less clear in self-employment. There is a relatively weaker education earnings gradient at least in part because more educated women work fewer hours when they become self-employed.[39]

The estimates from Table 5 show that there are important unobserved factors affecting wage and salary earnings. Around 53% of the population are type 1 individuals who are medium earners in both wage and salary and self-employment. Another 31% are type 2 women who are low wage and salary earners making on average 0.60 log points less than type 1 women. Type 2 women have medium earning ability in self-employment. Type 3 individuals make up 16% of the population and are high earners in both wage and salary and self-employment. These levels of heterogeneity in earning ability are similar in magnitude to those found in Francesconi (2002).

Overall, these earnings equations imply that self-employment experience is much better for future earnings than spending a year not employed. The comparison between a year of self-employment and spending a year in wage and salary employment is less clear. In general wage and salary experience has stronger effects on wage and salary earnings than self-employment experience, but self-employment experience has stronger positive effects on self-employment earnings.

[37] Light and Ureta (1995) prefer a model that keeps track of the percentage of each year a woman was employed and controls for the order of their employment history. I compare my results to the specification that is the most similar to mine, which uses cumulative actual experience. In this specification, they use a quadratic form, which is known to underestimate returns to very low levels of experience. This might explain why my estimates are much larger for 1 and 3 years. Additionally their study focuses on an earlier time period and controls for more covariates including job tenure.

[38] A preferred specification would be to keep track of when the employment gap occurred, but that would increase the computational burden of estimation substantially.

[39] OLS regressions on hourly wage rates confirm that women with Bachelor's degrees earn more than women with a high school education. OLS regressions on earnings are consistent with the structural parameters that women with Bachelor's degrees and women with high school degrees have similar earnings in self-employment.

5.3 Women's Utility

The estimates of the parameters from the second stage confirm that working has utility costs. The estimates from Table 6 show that self-employment is the relatively more costly employment type. I estimate that the there is a utility cost equivalent to $85,300 incurred the first time a woman enters self-employment. This entry cost can be thought of as the time and effort spent developing the business idea and gathering all the necessary material and licenses to become self-employed. There is an additional annual utility cost of $30,000 for each year spent working in self-employment. This cost represents a loss in leisure associated with working and additional stress associated with being self-employed. Working in wage and salary employment also has a utility cost of around $13,000 which similarly represents the loss of leisure and stress associated with working. These utility costs represent net costs so may also include positive traits associated with working, like a sense of accomplishment and having a social network of co-workers. A loss of fringe benefits might also contribute to the much larger net utility cost of self-employment relative to wage and salary employment.

While in general the utility costs of working in self-employment are higher than in wage and salary employment, the additional costs of working associated with having children are smaller in self-employment. I find that women whose youngest child is 0-5 years of age incur an additional cost of working in wage and salary employment of $10,700. The cost for these mothers in self-employment is around $3,700. I interpret this difference of $7,000 as the value of flexibility offered by self-employment for mothers with young children. This flexibility is also important for mothers whose youngest child is 6-9 years old, and they value it at around $3,100. These estimates are consistent with my hypothesis that wage and salary employment is more costly for mothers than self-employment. Additionally the lower value for women whose youngest child is 6-9 years of age is consistent with the idea that self-employment provides a means to take care of children when they require the most care.

I find that women value the same level of consumption less when working. This suggests all else equal women with higher earning husbands are less likely to work, which is consistent with general patterns of female employment and spousal income. I find that the effect of husband's income on employment is smaller in self-employment, which may partially reflect differences between women with high earning and low earning spouses in access to financial or human capital that make it easier to be self-employed. My estimate for the marginal utility of consumption in wage and salary employment of 0.93 is similar to Francesconi (2002) who estimates a value of 0.98 for full-time wage and salary employment and 0.94 for part-time wage and salary employment.

There is substantial heterogeneity in the parameter estimates on the value of children. I find that type 1 and type 3 individuals receive very similar utility from children, while type 2

individuals receive a lower value from children. In simulations, I find that type 2 women have more children overall because they have relatively low opportunity costs of having children. Additionally, type 2 women have lower utility levels because of their lower earning potential, and therefore the lower utility from children might represent a similar fraction of of their overall utility. Simulations of the model show that type 1 women have on average 1.87 children, type 2 women have 2.18 children, and the high earning type 3 women have 1.74 children.

I estimate the standard deviation of the utility shock to be \$21,500, which suggests that there is a relatively large role for unobserved factors to influence choices. This value represents around 60% of women's average wage and salary earnings and around 20% of their average annual utility. The size of this utility shock implies that there will be many instances where women make different choices from the one with the highest expected value because of a positive utility shock to one alternative. While a richer model could better explain women's choices and decrease the variance of the utility shock, I view this model as capturing the primary aspects of preference heterogeneity across women and the main differences between wage and salary employment and self-employment.

5.4 Model Fit

In this section, I show that simulated data created using the model can match the life-cycle patterns of women's employment and fertility choices and the distribution of their lifetime work experience in each employment type. Demonstrating the in-sample fit of my model provides confidence in the results from my counterfactual exercises.

In order to check the fit of the model, I simulate women's decisions using each woman's actual initial conditions at the beginning of the estimation period. Table 7 compares the overall percentages of women making each employment-fertility choice and their completed fertility between the real data and the simulated data. The model fits the overall distribution of choices very well and the distribution of children reasonably well given the quadratic functional form for the utility from children. Chi-squared tests fail to reject the model.

In order to investigate the life-cycle properties of the model, I plot the fraction of women making each choice as a function of their age. I compare the prevalence of the six choices over the lifecycle between the simulated choices and the NLSY79 data in Figure 3. The model fits the age profile for self-employment behavior pretty closely. The model over-predicts wage and salary employment among young individuals and under-predicts non-employment. In later ages, the pattern is reversed and the model under-predicts wage and salary employment and over-predicts non-employment. Chi-squared tests of the choices at each age reject the model at a 5% level for ages 18 to 20, but fail to reject the model from ages 21 through 50.

There are a number of reasons the model may not match employment choices at young ages. First, there are relatively few women in the sample at young ages because women do not enter the estimation until they are married and not enrolled in school.[40] Second, the women who are in the sample at young ages might be different along unobserved dimensions as well as observed characteristics. These women must not have attended a four-year college directly after high school and married relatively early.

Table 8 shows the year-to-year transitions implied by the simulated data from the model. In comparison to the transitions in the underlying data, shown in Table 4, we see that women are more likely to move between employment types. This is especially true for women in non-employment and self-employment. Figure 4 plots the distribution of the total number of years each woman made each choice over her lifetime. These diagrams show that the simulated data fit the distribution of time spent in self-employment and non-employment, but do not have enough individuals with very low levels of wage and salary employment. Overall the model, while not perfect, fits the life-cycle pattern of fertility and employment choices from the data relatively well.

5.5 Implications of Modeling Simplifications

I make a number of simplifications to balance computational tractability with realism. Some of the most important simplifications are not allowing savings, not allowing for uncertainty in future job prospects, and not modeling the intensive labor supply decision.

My model abstracts from the savings and borrowing decisions, by assuming that women consume all of their income in every year. If women in fact are working in order to save for their retirement, this incentive could make working look more attractive and make the cost to working parameter, β_2^j, more positive. If there is little heterogeneity in the preference for saving for retirement in my population, this will not cause bias in the other parameters. The magnitude of this bias may be smaller for married women because on average their earnings make up only around a third of household income.

Second, my model does not incorporate the risk of job loss or unemployment. To the extent that unemployment spells are short, these will be reflected in lower earnings. By including the unemployment rate in the earnings equation, I account for more frequent unemployment spells during downturns. Additionally, the risk of job loss makes work less attractive because the returns to experience may never fully materialize. This consideration will be reflected in lower utility of work estimates.

The omission of savings and earnings risk interact. Including one without the other is

[40] Around 5% of the sample enters at age 18, 6% at age 19, and 9% at age 20. By age 20, 20% of the sample is present.

likely to have small effects on the parameter estimates, but including both could change the incentives reflected in the model substantially. If women see riskiness in their future income stream and have the ability to save, we might see a lot more employment at young ages to gain a buffer stock to insure against future shocks. While these are interesting incentives to investigate, they are beyond the scope of this paper. If this incentive to work to gain savings is large β_2 could be positively biased. If these working years coincide with having young kids at home, β_3 and β_4 could also be positively biased.

Finally, this paper focuses on the extensive margin of work by allowing women to be employed or not. I abstract from modeling the choice of hours or the characteristics of flexibility within a particular job. I think that this omission could be particularly relevant for my population of interest if women with young kids select into jobs within each type of employment that require lower numbers of hours or have other features that might be more important to women with young kids. For example, women with young kids have shorter commutes on average, which could reflect their desire to work closer to home.[41] There is also evidence that at least part of the motherhood penalty is attributable to part-time work and family friendly jobs (Gangl and Ziefle (2009), Budig and England (2001)). To the extent that the average job for women with young kids is lower paying, I will overestimate earnings among women with young children. This leads to a negative bias in the parameters that estimate the costs of working associated with having young children, β_3 and β_4. If the self-employed and wage and salary employed react differently to the presence of a young child, this could bias my estimate of the value of flexibility. For example, suppose that the self-employed are more able to adjust their hours downward in response to having a child, then the self-employment disutility of work term will be too negative and the value of self-employment flexibility will be underestimated. If instead, self-employment allows women to maintain their level of hours better than wage and salary employment while still caring for children, the self-employment flexibility will be overestimated.

In order to estimate the sign and potential effect of this omission, I examine whether the earnings residuals vary differentially with the presence of young children for women in self-employment and wage and salary employment. Specifically, I regress an indicator for self-employment status, an indicator for having a youngest child ages 0 to 5 and one for having a youngest child 6 to 9 years of age, and the interactions between self-employment and age of child indicators on the earnings residuals.[42] I find that the earnings for mothers in general are over-predicted. I find that the earnings for mothers in self-employment with preschool-aged children are even more over-predicted than wage and salary employment, but

[41] Author's calculates from IPUMS 5% microsample of the US Census and see Black et al. (2014).

[42] The regression results can be found in the appendix Table A6.

that earnings for mothers in self-employment who have a youngest child ages 6-9 years of age are less over-predicted than in wage and salary employment. The signs of the estimates suggest that the value of self-employment flexibility for women with children between the ages of 0 and 5 is underestimated and that the value of self-employment flexibility for women with children between the ages of 6 and 9 is overestimated. Neither of the interaction terms are statistically significant and the estimates are quite noisy so it's difficult to evaluate how large the bias is likely to be.

Overall, I do not think that the omission of modeling job characteristics or the hours decision is likely change the overall qualitative conclusion of the paper that self-employment represents a more flexible option for mothers with young children.

5.6 Discussion of Alternative Interpretations

In this paper, I interpret the difference in the costs of working associated with having young children between wage and salary employment and self-employment as the value of self-employment flexibility. In this section I discuss three potential alternative explanations for this difference besides workplace flexibility. These different interpretations identify factors that change differentially between the two employment types when women have children.

First, mothers may use self-employment as a way to avoid discrimination in the wage and salary employment sector, which would make self-employment appear relatively more attractive to mothers. While previous research has established that a motherhood penalty in earnings exists, the amount of the penalty due to discrimination appears to be relatively small. For example, Gangl and Ziefle (2009), argue that almost all of the motherhood wage penalty can be explained by changes to part-time or family friendly positions and time spent out of the labor force. My model explicitly takes into account time spent not employed, and I discuss the potential impact of family friendly positions in the previous section. While employer discrimination against mothers may exist, it is unlikely to account for a large portion of the difference in the utility costs of working associated with young children between the two employment types.

Second, having children may prompt women to become self-employed to pass their business on to their children, which would increase the value of self-employment relative to wage and salary employment for women with kids. This explanation is unlikely to drive the difference in the costs of working associated with having young children because women's self-employment behavior is not consistent with this motivation. Only 1.6% of US businesses are inherited (Fairlie and Robb (2007)), and relatively few women in my data remain self-employed for the duration of their careers. The majority of the types of businesses in the data are not ones that are typically inherited: housekeeping, child care, hairdressers.

Finally, my results suggest that self-employment is most valuable to women with preschool aged children and less valuable to school aged children, a pattern that is not implied by a desire to pass on a business to children.

Third, having young children could lower a woman's tolerance for risky work actually making self-employment less attractive to mothers.[43] This effect would bias my estimates the opposite direction, making them an underestimate of the value of flexibility. However, the women in my sample may be relatively more shielded from this income risk because the majority of them are the secondary earner in the household.

While there are alternative explanations that could be contributing to the higher self-employment rates among mothers of young children, there is relatively strong descriptive evidence to support additional flexibility within self-employment as the key causal factor. Overall, the evidence to support becoming self-employed to avoid workplace discrimination or pass on a business is much weaker. These motivations could contribute to the benefits of self-employment for mothers, but the majority of the effect is likely to still be due to a desire for flexibility.

6 Counterfactual Exercises

In this section, I describe three partial equilibrium counterfactual exercises I conduct using the model. Together these exercises provide evidence that workplace flexibility influences women's employment and fertility decisions, which in turn affect their lifetime utility and earnings.

6.1 Value of Self-Employment Flexibility

In my first counterfactual, I estimate the value of self-employment flexibility by assuming that mothers with young children in self-employment face the same utility costs of working as mothers in wage and salary employment. Specifically, I set a new value for the disutility of working in self-employment with a preschool-aged child, $\tilde{\beta}_3^{se}$, to equal the estimated utility cost in wage and salary employment, β_3^{ws}. I do the same for the cost of working associated with having children 6 to 9 years of age: $\tilde{\beta}_4^{se} = \beta_4^{ws}$. I interpret the difference between the estimated model and this counterfactual as quantifying the impact of the additional flexibility mothers receive in self-employment.

[43] Self-employment earnings among men have been shown to have higher unconditional variance than wage and salary earnings and therefore might represent a more risky employment option (Evans and Leighton (1989), Hamilton (2000)). In my data, self-employment earnings actually have a lower variance, which might be explained by my focus on married white women.

I find that self-employment flexibility is a big motivator for women to become self-employed. Table 9 provides a summary of how the counterfactual exercises affect women's earnings, work experience, fertility and utility. Without the additional flexibility, self-employment rates fall from 7.1% to 4.0%. The availability of self-employment flexibility increases fertility by around 2.6%. This estimate is similar in magnitude to Adda et al. (2011) who find that doubling the annual cash transfer per child in Germany would increase fertility by 2% in the long run.

I estimate that self-employment flexibility raises the present value of women's median lifetime earnings by 2.5%. As Figure 5 shows, this increase in lifetime earnings is concentrated in the lower portion of the lifetime earnings distribution. Among women who were induced to be self-employed by the additional flexibility, I find that the majority of the increase in lifetime earnings arises from years that women decided to work in self-employment rather than not work. Among women who became self-employed because of the additional flexibility, 70% of their increased earnings came from years when they moved from non-employment to employment. The remaining 30% came from increases in earnings in years when individuals worked under both the baseline and the counterfactual. These results are consistent with Adda et al. (2011) who find that the biggest earnings cost associated with having children are the lost earnings while not working, not lower earnings due to atrophied skills or lower work experience.

The impact of self-employment flexibility on the gender earnings gap combines two opposing effects. First, self-employment flexibility increases work experience among women raising their earning potential and lowering the gender earnings gap. Second, it encourages women to move from relatively higher earning wage and salary employment to self-employment and encourages relatively low ability and low earning women to move from non-employment to self-employment. These changes reduce the average observed earnings among working women and actually increase the gender earnings gap.

These two opposing effects dominate at different points over the life-cycle. Figure 6 shows the median earnings for employed women in the baseline and in the inflexible self-employment counterfactual. Self-employment flexibility lowers the median earnings of women who work between the ages of 18 and 42 and raises them above age 42. At younger ages when women are likely to have young children at home, the self-employment flexibility is encouraging low earning women to work and inducing women to switch to self-employment to gain flexibility. At older ages, there is less selection in which women work because the costs to working are reduced when women no longer have young children at home. Additionally, older women's earnings are higher in the baseline because they have more work experience due to self-employment flexibility.

Overall, my results suggest that self-employment flexibility does not change the observed gender earnings gap because the positive effects of additional work experience are canceled out by additional years spent in a lower earning employment type and increased participation among lower earning women. These results suggest that the gender earnings gap is an important, but sometimes misleading measure. A policy that reduces the observed gender earnings gap is not necessarily good for women's earnings if it increases average earnings by encouraging low-earning women to leave the labor force.

I estimate a much smaller effect of self-employment flexibility on women's utility; it increases utility by 0.12%. In order to benefit from the added flexibility in self-employment, I estimate that women have to pay high utility costs to become and stay self-employed. Therefore, when self-employment becomes less flexible, those women lose out on the flexibility but they also no longer have to pay the large costs of becoming self-employed. Women who decide not to be employed gain in leisure and women who decide to work in wage and salary employment pay a much lower cost of working. These results suggest that the evaluation of policies should consider changes to leisure and home production in addition to changes in earnings.[44]

6.2 More Flexible Wage and Salary Employment

In this section, I estimate how women's choices change if wage and salary employment is as flexible as self-employment. This counterfactual simulates implementing a set of policies within wage and salary employment to mimic the flexibility offered in self-employment. I simulate the model with a new value for the disutility of working in wage and salary employment with a preschool-aged child, $\tilde{\beta}_3^{ws}$, that equals the estimate for the utility cost of working in self-employment, β_3^{se}. I do the same for the utility cost of working associated with having a child between the ages of 6 and 9 by defining a new cost in wage and salary: $\tilde{\beta}_4^{ws} = \beta_4^{se}$. These estimates represent an upper bound on the positive impacts of enacting policies that make wage and salary employment comparably flexible to self-employment because these policies have costs to employers and would likely result in lower wages for women if they were implemented on a large scale.[45]

I find that increasing wage and salary employment flexibility would increase women's

[44] See Greenberg and Robins (2008) on the importance of accounting for the value of non-market time in cost-benefit analyses.

[45] See Pitt-Catsouphes et al. (2007) for details on employers' biggest barriers to flexible work policies. There may, however, exist policies that could make wage and salary employment more flexible than self-employment. There are many occupations within self-employment that lack certain types of flexibility. For example, see Goldin and Katz (2012) for a description of how pharmacists find more flexibility in wage and salary employment.

median lifetime earnings by 7.6%. In contrast to flexibility in self-employment, Figure 7 shows that flexibility in wage and salary employment raises median earnings among employed women throughout the life-cycle. I estimate that this policy unambiguously reduces the gender earnings gap, by raising employed women's median earnings by 2.6%. This change implies a movement in the observed gender gap in median earnings from 22% to 19%. When wage and salary employment is more flexible, the fraction of years that women spend not employed falls from 26.5% to 24.0% as women are encouraged to continue working even when they have young children at home. Self-employment rates also fall from 7.1% to 5.2% because self-employment is not longer needed as a flexible work option. Women's average fertility rises from 1.95 to 2.46 children, which represents a very large increase in fertility. Increasing workplace flexibility increases women's utility by around 1.7%.

Overall, this exercise points to potentially large benefits to women from making workplaces more flexible. These benefits to workers can help explain an increasing trend in firms offering telecommuting options, flexible schedules, job sharing, and parental leave. Unfortunately, there are also many barriers to implementing flexible work policies. Top concerns among employers include fears about monitoring employees, a loss in productivity, and treating all employees fairly (Pitt-Catsouphes et al. (2007)). There are also legal issues making it difficult for employers to track hourly non-exempt employees if they work varied schedules or work from home (Yager (2014)). Finally, there are some businesses that operate under a more traditional culture, where managers don't promote the implementation of flexible policies (SHRM (2010)).

These results provide a benchmark for understanding the potential benefits of increasing flexible work policies. They complement previous survey evidence, which shows that around 70% of working mothers said schedule flexibility was extremely important to them (Parker and Wang (2013)). Given current evidence that the gender earnings gap arises when women have children, policies targeted to benefit parents when they have young children are likely to be particularly effective in addressing the earnings gap. Additionally, these results suggest that workplace flexibility can encourage fertility, which could be important for countries trying to increase or maintain their fertility rates.

6.3 Decrease Barriers to Female Self-Employment

In this section, I estimate the impact of a policy to reduce the utility cost of entering self-employment by 10%. This counterfactual represents any intervention that lowers the barriers to entering self-employment for women. In response to some evidence that women and minorities have more difficulty accessing capital and business networks to start a business, there have been targeted programs to increase business ownership among these groups (Barr

(2015)). These policies include expanding small business loans backed by the Small Business Association, and grants to provide training programs and improve connections between successful and prospective business owners. An evaluation of these types of programs is beyond the scope of this paper, but this counterfactual highlights the potential impacts of policies that successfully lower the entry costs of self-employment for women.[46] Licensing requirements to operate a business or work in a profession also represent entry costs that policies could reduce to encourage self-employment among all groups. The self-employed are more likely to be licensed workers (Council of Economic Advisors (2015)). Getting a license can include completing training courses, passing an inspection, and filling out the appropriate paperwork to start a business (Kleiner (2013)). There might be ways that governments can streamline these processes or only keep the aspects of licensing necessary to maintain consumer safety (Council of Economic Advisors (2015)).

As shown in Table 9, I find that reducing the entry cost to self-employment increases self-employment rates by 30% and increases median lifetime earnings by 1.7%. The policy has very little effect on fertility rates and raises lifetime utility by 0.12%. These results suggest that measures that reduce the costs of becoming self-employed for women would increase their self-employment rates substantially, but would not influence fertility by as much. Reducing the entry costs of self-employment has similar effects on the gender earnings gap as self-employment flexibility. It increases it slightly at younger ages and decreases it at older ages, with little overall effect. Advocates of policies encouraging female self-employment often have in mind promoting female entrepreneurship in high growth industries. An intervention of this type could potentially have much larger impacts on women's earnings because it may help women improve their earnings growth rates. The counterfactual presented here simulates the average female self-employment experience, which tends to be relatively slower growth areas such as child care or housekeeping.

7 Conclusion

As the share of households with working mothers continues to rise, workplace flexibility has become increasingly important. In this paper, I estimate a life-cycle model of married women's fertility and labor supply. My results provide evidence that workplace flexibility influences married women's fertility and employment decisions. I show that on average self-

[46] In general, as Barr (2015) and Michaelides and Benus (2012) mention, many programs do not have rigorous evaluations of their impact on outcomes. In particular, there has been a lot of focus on helping the unemployed become self-employed. Michaelides and Benus (2012) analyze a policy to promote self-employment among individuals who are employed, unemployed and out of the labor force and find no effects for non-unemployed individuals.

employment imposes smaller additional costs of working on mothers with young children than wage and salary employment. My estimates suggest that women with preschool-aged children value the additional workplace flexibility of self-employment at around $7,000 per year. Flexibility appears to be an important motivation for becoming self-employed. I estimate self-employment rates would decline by over 40% if self-employment were no more flexible for mothers than wage and salary employment.

My partial equilibrium counterfactual exercises suggest that policies to target flexibility within wage and salary work could have large positive effects on women's earnings, fertility and employment. I find that self-employment flexibility raises women's work experience and lifetime earnings, but has little effect on the overall gender earnings gap. In contrast, increases in the flexibility for mothers within wage and salary employment are estimated to decrease the gender earnings gap from 22% to 19%. Because wage and salary employment is much more common than self-employment, focusing on flexibility in that type of employment is likely to bring the most widespread benefits to women.

A task for future research is to quantify the potential negative consequences of workplace flexibility, including discrimination against women viewed as likely to use such policies.[47] If making workplaces more flexible causes women's wages to fall substantially, the benefits outlined in this paper may be offset by lower lifetime earnings. Indeed, Blau and Kahn (2013) provide suggestive evidence that American women outpace their OECD counterparts in attaining highly paid management positions and one potential explanation is that the family friendly policies offered by other countries segment women into low-earning part-time positions.

Workplace flexibility is inherently a multidimensional concept, but further documentation of the types of policies firms are offering and the policies actually utilized by workers would help clarify the state of workplace flexibility in the US. Additional research should also focus on potential interactions between policies. For example, a policy implementing a flexible work schedule might be more effective for mothers when it is combined with paid maternity leave. Finally, additional research is needed to understand whether policies that allow both women and men to better manage work and family responsibilities could have positive effects on marriage quality and children's wellbeing.

[47] See Blau and Kahn (2013) for a discussion of the benefits and costs of "family friendly" policies. See Gruber (1994), Prada et al. (2015), Thomas (2014), and Fernández-Kranz and Rodríguez-Planas (2013) for evidence of the effect of specific policies on women's wages.

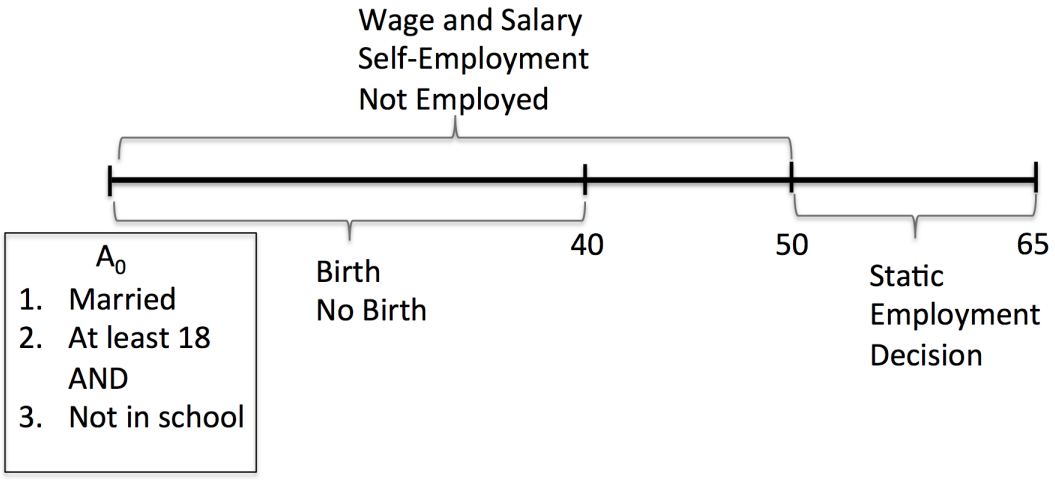
8 Tables and Figures

Table 1. Top Jobs Among Self-Employed Women in Sample; NLSY79

Type of Job	**Fraction of Self-Employed**
Child Care Workers	21.5
Administrative (Bookkeeping, Secretarial)	9.6
Managers	7.8
Sales	6.7
Housekeepers	5.3
Education	4.3
Hairdressers	4.0
Arts (Designer, Writer, Musicians)	3.7
Total	62.9

Notes: Data are from the NLSY79. Sample includes self-employed white married women from the estimation sample.

Figure 1. Model Timing Description



Notes: Figure shows the relevant decisions at each age in the model.

Table 2. Summary Statistics of Estimation Sample

Year-Individual Observations	N=23,839	
	Mean	**Standard Deviation**
Age	35.4	7.8
Earnings (2000$) Wage & Salary[1]	36,761	49,587
Earnings (2000$) Self-Employed[1]	23,114	34,830
Husband's Earnings (2000$)	64,287	117,344
	Median	
Earnings (2000$) Wage & Salary[1]	25,157	
Earnings (2000$) Self-Employed[1]	13,908	
Husband's Earnings (2000$)	40,677	
Individual Observations	N=1,083	
	Mean	**Standard Deviation**
HS or Less	41.4	.
Some College	23.5	.
Bachelor's	35.1	.
Number of Children	1.95	1.09
Age at Beginning of Estimation	25.0	5.4
Years of Estimation	26.2	5.2
Prior Wage & Salary Experience	3.6	4.4
Prior Self-Employment Experience	0.1	0.8
Prior Years Not Employed	0.5	1.5
Total Wage & Salary Experience	17.5	8.1
Total Self-Employment Experience	1.5	3.3
Total Years Not Employed	6.4	6.9
Ever Self-Employed	28.1	.

[1] Only includes observations who worked in that type of employment.

Notes: Summary statistics cover the estimation period only. Data are from the NLSY79.

Table 3. Percent of Observations Making Each Choice by Age of the Mother and the Number of Children

	Wage & Salary		Self-Employed		Not Employed		N
	No Birth	Birth	No Birth	Birth	No Birth	Birth	
All Ages	62.2	3.7	6.0	0.4	23.8	3.8	23,839
18-25	53.3	5.6	2.4	0.3	28.1	10.4	2,971
26-30	54.4	8.2	5.2	0.9	23.7	7.7	4,169
31-35	58.6	5.8	6.7	0.8	24.0	4.1	4,743
36-40	65.8	2.0	6.4	0.4	23.7	1.8	4,811
41-50	70.6	0.0	7.4	0.0	22.0	0.0	7,145
Number of Kids							
0	68.3	7.5	4.6	0.6	13.0	6.0	5,387
1	55.8	6.8	5.2	0.8	24.0	7.4	4,846
2	64.7	1.2	5.5	0.2	26.5	1.9	8,593
3	57.7	0.6	9.2	0.3	30.7	1.6	3,321
4	53.2	0.0	9.0	0.0	37.8	0.0	1,232

Notes: Table includes observation-years during the estimation period. Data are from the NLSY79.

Table 4. Annual Transitions Across Choices

		Choice in Period $t+1$						
		Wage & Salary		Self-Employed		Not Employed		Row Percent
Choice in Period t		No Birth	Birth	No Birth	Birth	No Birth	Birth	of total
Wage & Salary	No Birth	86.2	5.3	1.4	0.2	5.0	1.9	61.9
	Birth	85.2	2.6	2.6	0.1	7.6	1.8	3.9
Self-Employed	No Birth	13.3	1.2	72.1	5.2	6.9	1.3	6.0
	Birth	16.2	1.0	73.3	0.0	8.6	1.0	0.5
Not Employed	No Birth	15.1	1.1	2.1	0.2	72.0	9.6	23.8
	Birth	16.2	0.4	1.8	0.1	75.7	5.8	4.0

Notes: Table includes observation-years during the estimation period only. Data are from the NLSY79.

Table 5. Log Earnings Parameter Estimates

Wage and Salary Log Earnings			Self-Employment Log Earnings		
Description	Estimate	Standard Error	Description	Estimate	Standard Error
Wage and Salary Experience-Linear Spline			Wage and Salary Experience-Linear Spline		
1-2 Years	0.160*	(0.025)	1-5 Years	-0.008	(0.005)
3-5 Years	0.035*	(0.011)	6-10 Years	0.012*	(0.004)
6-10 Years	0.035*	(0.004)	11-20 Years	-0.0001	(0.003)
11-15 Years	0.050*	(0.003)	21 or More Years[1]	0.047	(0.033)
16-23 Years	0.030*	(0.002)			
24 or More Years[1]	0.027*	(0.010)			
Self-Employment Experience-Linear Spline			Self-Employment Experience-Linear Spline		
1-2 Years	0.022*	(0.003)	1-2 Years	0.033	(0.052)
3-9 Years	0.026*	(0.002)	3-9 Years	0.037*	(0.015)
10 or More Years[1]	0.110*	(0.014)	10 or More Years[1]	0.695*	(0.081)
Years Not Employed-Linear Spline			Years Not Employed-Linear Spline		
1 Year	-0.085*	(0.003)	1 Year	-0.091*	(0.011)
2-9 Years	-0.021*	(0.001)	2-9 Years	-0.043*	(0.004)
10 or More Years[1]	0.014*	(0.006)	10 or More Years[1]	0.055*	(0.027)
Unemployment rate	-0.017*	(0.004)	Unemployment rate	-0.027*	(0.011)
Some College	0.080*	(0.009)	Some College	0.067*	(0.016)
Bachelor's Degree	0.132*	(0.008)	Bachelor's Degree	0.139*	(0.019)
Type 2	-0.604*	(0.010)	Type 2	0.023	(0.021)
Type 3	0.600*	(0.009)	Type 3	0.639*	(0.024)
Intercept	-2.012*	(0.045)	Intercept	-2.195*	(0.094)
Fraction Type 1	53.0*	(1.906)			
Fraction Type 2	31.2*	(1.750)			
Fraction Type 3	15.8	-			

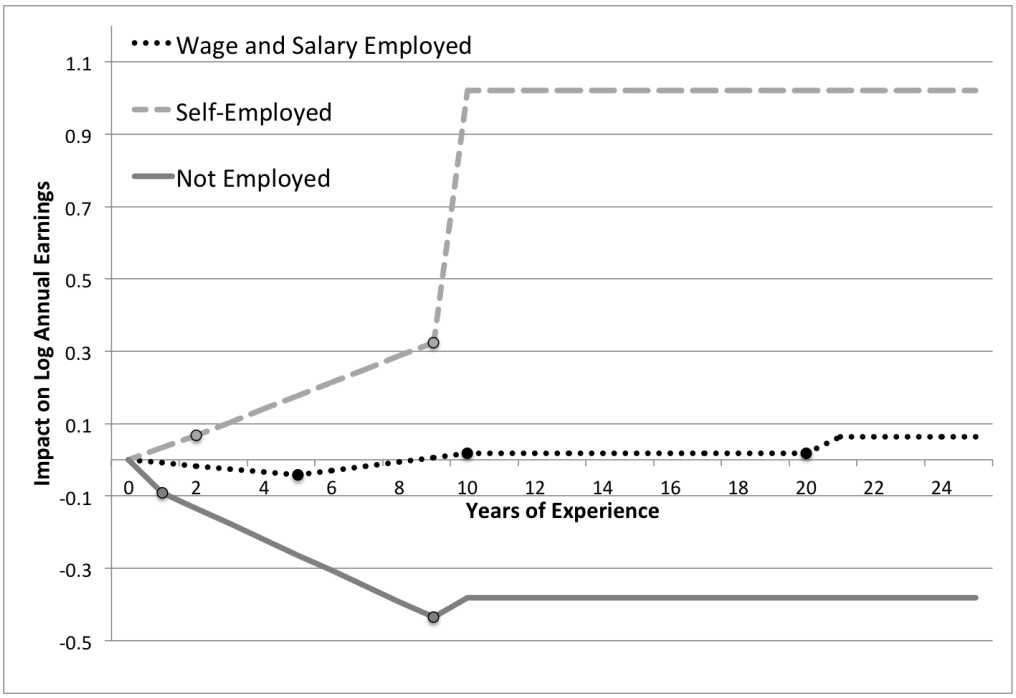
	Ratio Wage and Salary Earnings	Ratio Self-Employment Earnings
Workers with X years of wage and salary experience versus workers with none:		
3 Years	1.36	0.97
10 Years	1.60	1.02
15 Years	1.85	1.02
Workers with X years of self-employment experience versus workers with none:		
1 Year	1.02	1.03
3 Years	1.07	1.10
5 Years	1.12	1.18
Workers with X years of non-employment versus workers with none:		
1 Year	0.92	0.91
3 Years	0.87	0.82
5 Years	0.83	0.74

Notes: Estimates are from maximum likelihood estimation.

1. Top experience categories are just indicators for having experience levels at or above that cutoff essentially flattening out the earnings profile. Predicted log earnings are denominated in 100,000s of $2000. Standard errors are calculated using the Fisher information matrix. *p<0.05

Figure 2. Implied Effect of Experience on Earnings

(a) Wage and Salary



(b) Self-Employment

Notes: Figures show how different levels of experience in the three employment choices affect women's expected earnings in wage and salary employment and self-employment. The levels are all relative to having 0 years in that employment type. Plots come from the earnings parameters estimates in Table 5. Dots denote nodes of the piece-wise linear function.

Table 6. Utility Parameter Estimates

Parameter	Description	Estimate	Standard Error
β_1^{ws}	Marginal Utility Consumption W-S	0.93	(0.002)
β_1^{se}	Marginal Utility Consumption S-E	0.98	(0.003)
β_2^{ws}	Working in W-S	-13,049	(282)
β_2^{se}	Working in S-E	-29,908	(841)
β_3^{ws}	Youngest Child 0-5 W-S	-10,684	(324)
β_3^{se}	Youngest Child 0-5 S-E	-3,696	(642)
	Difference	-6,988	(719)
β_4^{ws}	Youngest Child 6-9 W-S	-6,023	(569)
β_4^{se}	Youngest Child 6-9 S-E	-2,952	(1,025)
	Difference	-3,071	(1,172)
β_5^{se}	Entry to S-E	-85,276	(3,024)
	Linear Children Term-Type 1	3,487	(152)
β_6	Linear Children Term-Type 2	1,444	(164)
	Linear Children Term-Type 3	3,699	(247)
	Quadratic Children Term -Type 1	-925	(36)
β_7	Quadratic Children Term -Type 2	-521	(38)
	Quadratic Children Term -Type 2	-919	(67)
$\frac{\rho\pi}{\sqrt{6}}$	Standard Deviation ϵ	21,517	(388)
	Log Likelihood	-37,567	

Notes: These estimates come from the second stage maximum likelihood estimation. Parameter values are denominated in 2000$ except for the marginal utility of consumption parameters.

Table 7. Model Fit-Overall Choices and Fertility

Choices	**Data**	**Model**
Wage and Salary, No Birth	62.2	62.6
Wage and Salary, Birth	3.7	3.8
Self-Employment, No Birth	6.0	6.6
Self-Employment, Birth	0.4	0.5
Not Employed, No Birth	23.8	23.8
Not Employed, Birth	3.8	2.6
Completed Fertility		
0	12.7	11.5
1	15.9	17.8
2	44.4	39.4
3	18.9	26.3
4	8.0	5.0

Notes: Table compares overall distribution of choices and completed fertility implied by the model with the data.

Table 8. Annual Transitions Across Choices Simulated Model

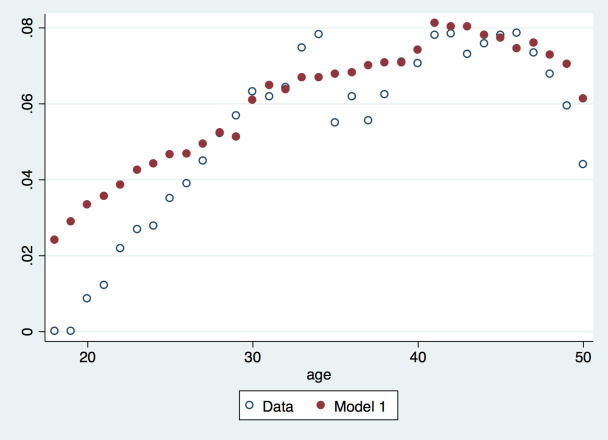
		Model						
		Choice in Period $t+1$						
		Wage & Salary		Self-Employed		Not Employed		
Choice in Period t		No Birth	Birth	No Birth	Birth	No Birth	Birth	Row Percent
Wage & Salary	No Birth	74.5	3.3	4.3	0.3	16.2	1.5	62.4
	Birth	53.5	16.2	4.2	1.1	20.2	4.9	4.0
Self-Employed	No Birth	40.8	1.9	36.1	2.4	17.6	1.3	6.6
	Birth	27.9	8.4	33.6	7.9	18.3	4.0	0.6
Not Employed	No Birth	43.4	2.5	5.0	0.3	44.4	4.4	23.7
	Birth	29.5	7.0	3.8	1.0	48.6	10.0	2.8

Notes: Table shows transitions in choices from simulated data using the estimates from Table 5 and Table 6. The simulated choices are calculated using the estimates to simulate the model 20 times for each woman. Each woman starts with her actual initial conditions but makes decisions according to the model with the estimated parameters.

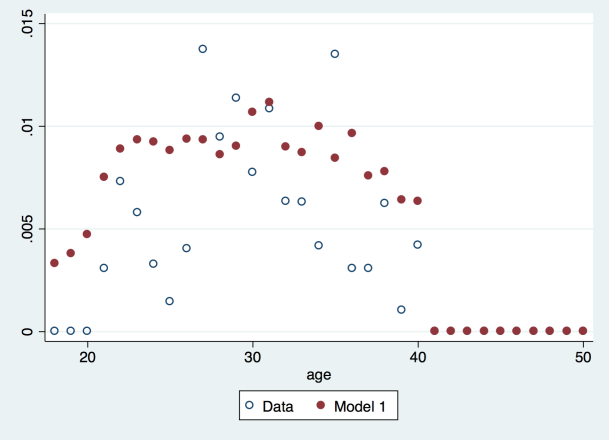
Figure 3. Choices Over the Life-Cycle; Model v. Data

(a) Wage and Salary; No Birth

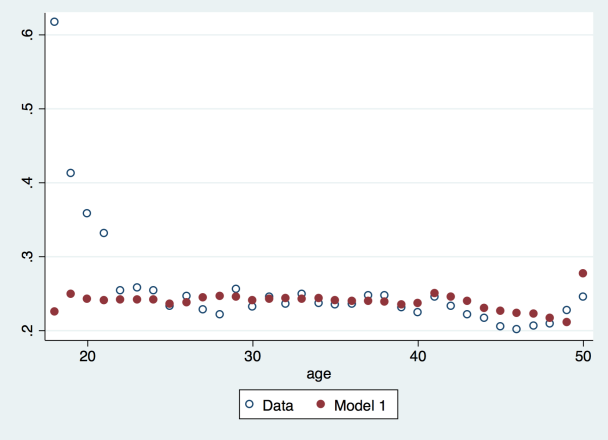
(b) Wage and Salary; Birth



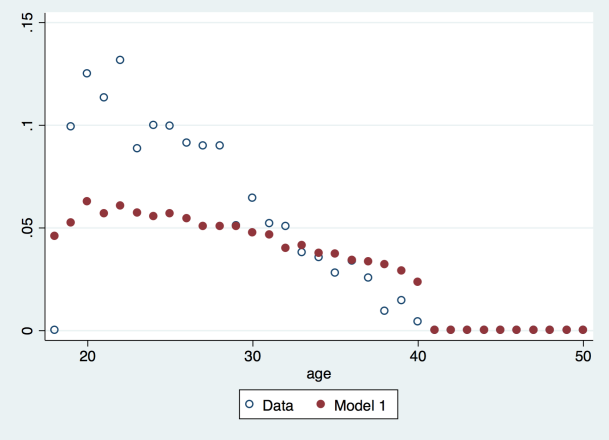
(c) Self-Employed; No Birth



(d) Self-Employed; Birth



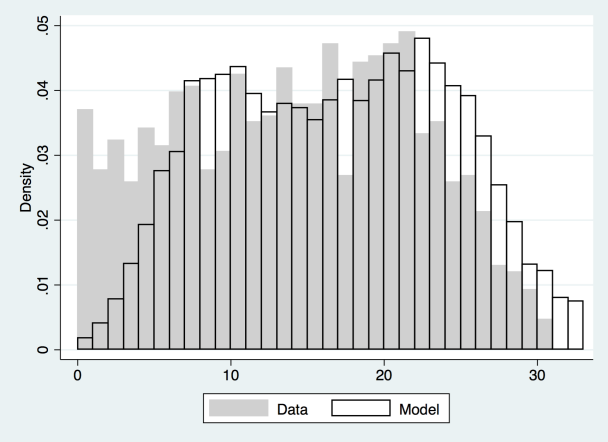
(e) Not Employed; No Birth



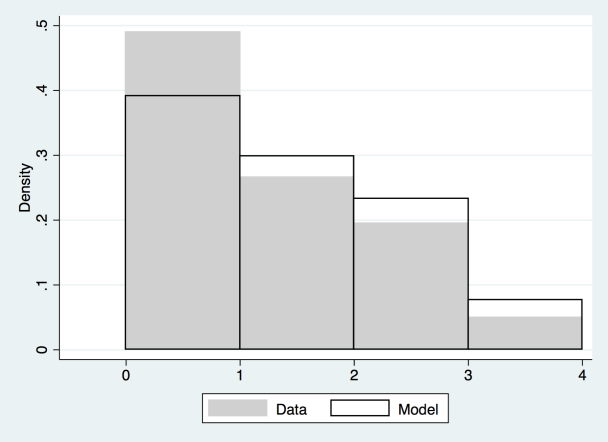
(f) Not Employed; Birth

Notes: Figures show the proportion of individuals at each age choosing each of the six possible fertility-employment choices from the data and from simulations from the model.

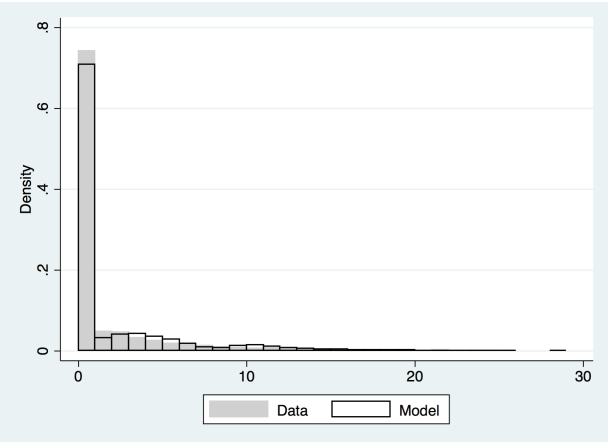
Figure 4. Cumulative Years Choices; Model v. Data



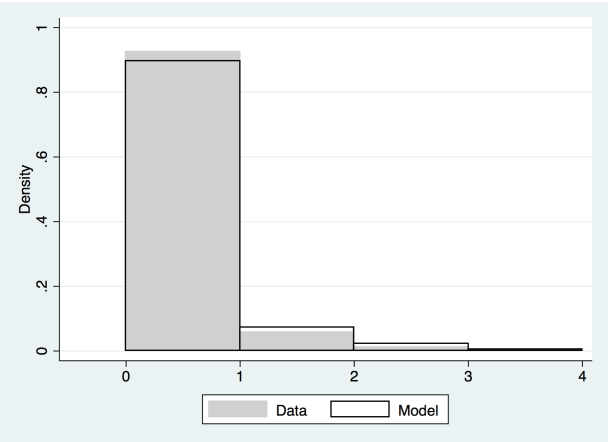
(a) Wage and Salary; No Birth



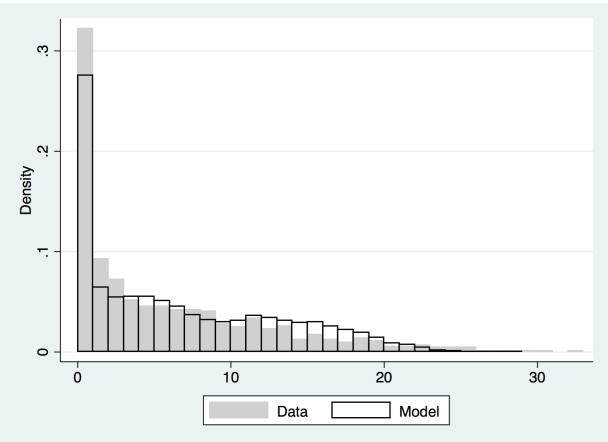
(b) Wage and Salary; Birth



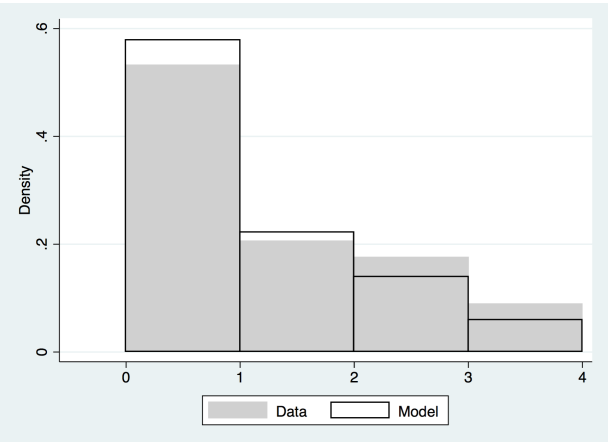
(c) Self-Employed; No Birth



(d) Self-Employed; Birth



(e) Not Employed; No Birth



(f) Not Employed; Birth

Notes: Figures show the distribution of the total number of years each woman made each of the six possible fertility-employment choices from the data and from simulations from the model.

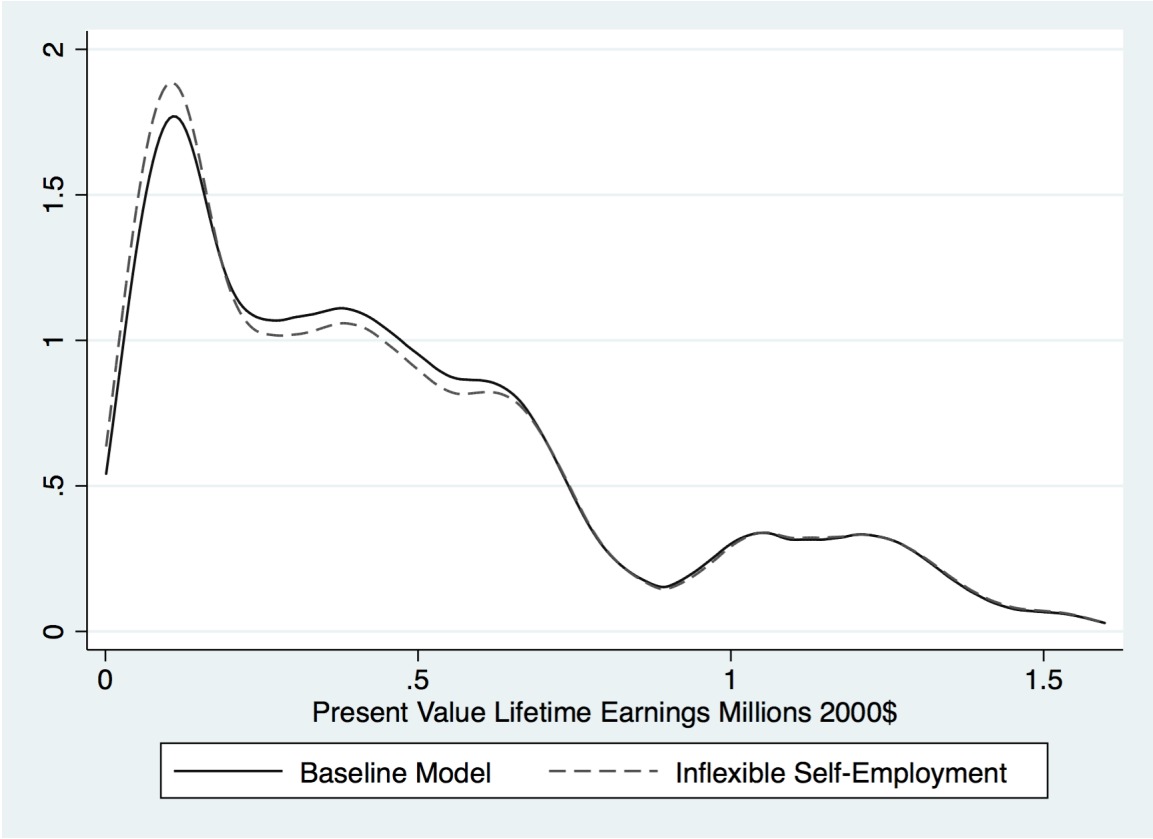
Table 9. Effect of Counterfactual Exercises on Fertility, Earnings, Employment and Utility

	Model Baseline	**Inflexible Self-Employment**	**Flexible Wage and Salary Employment**	**10 Percent Lower Self-Employment Entry Cost**
Total Fertility	1.95	1.90	2.46	1.95
Pct Ever Self-Employed	30.1	22.1	25.3	40.1
PV Median Lifetime Earnings (Thousands 2000$)	392.2	382.3	422.0	399.0
Percent Change in PV Median Lifetime Earnings		-2.5	7.6	1.7
	Fraction in Each Employment Type			
Wage & Salary	66.4	67.9	70.8	65.4
Self-Employment	7.1	4.0	5.2	9.3
Not Employed	26.5	28.1	24.0	25.3

	PV Lifetime Utility (Millions 2000$)	**Percentage Change Relative to Baseline**		
All	1.59	-0.12	1.73	0.12
High School or Less	1.27	-0.12	2.11	0.13
Some College	1.44	-0.13	1.92	0.13
Bachelor's Degree	2.04	-0.11	1.36	0.10

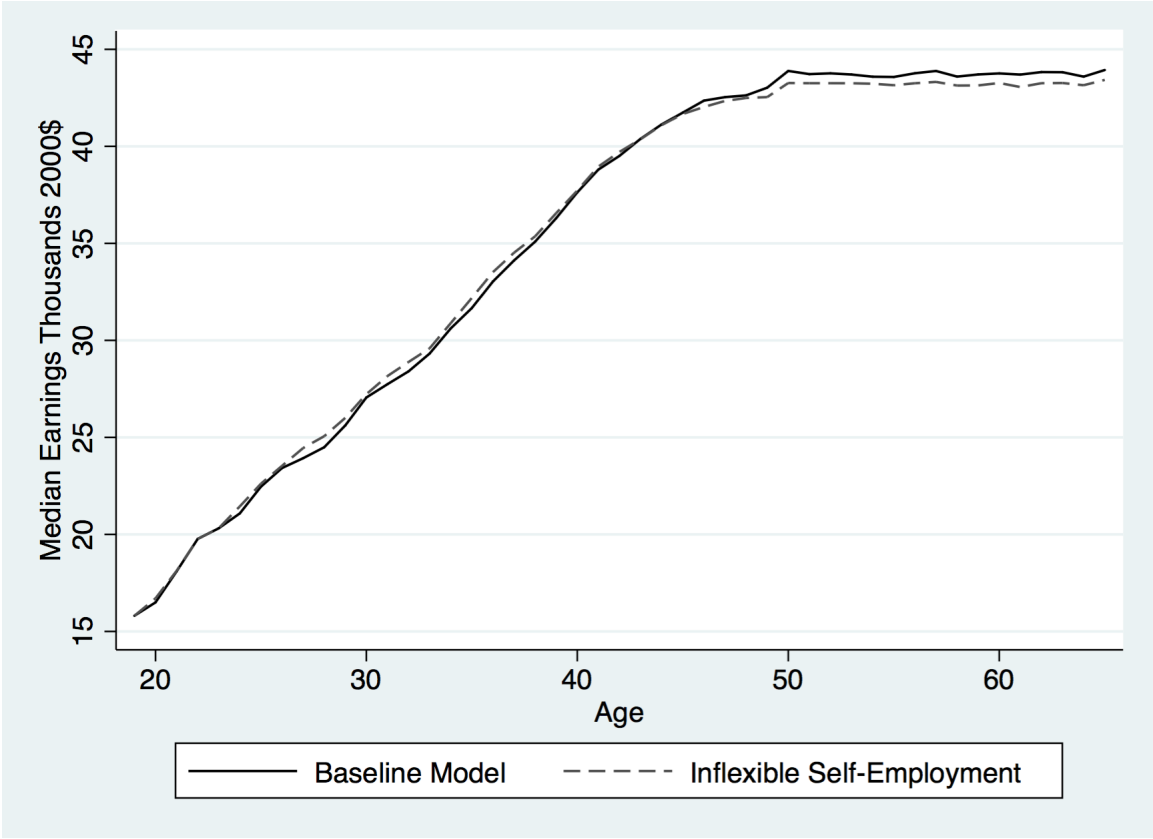
Notes: Estimates come from comparing simulated data from the baseline model to simulated data under three counterfactual exercises.

Figure 5. Distribution of Present Value Lifetime Earnings: Baseline and Inflexible Self-Employment



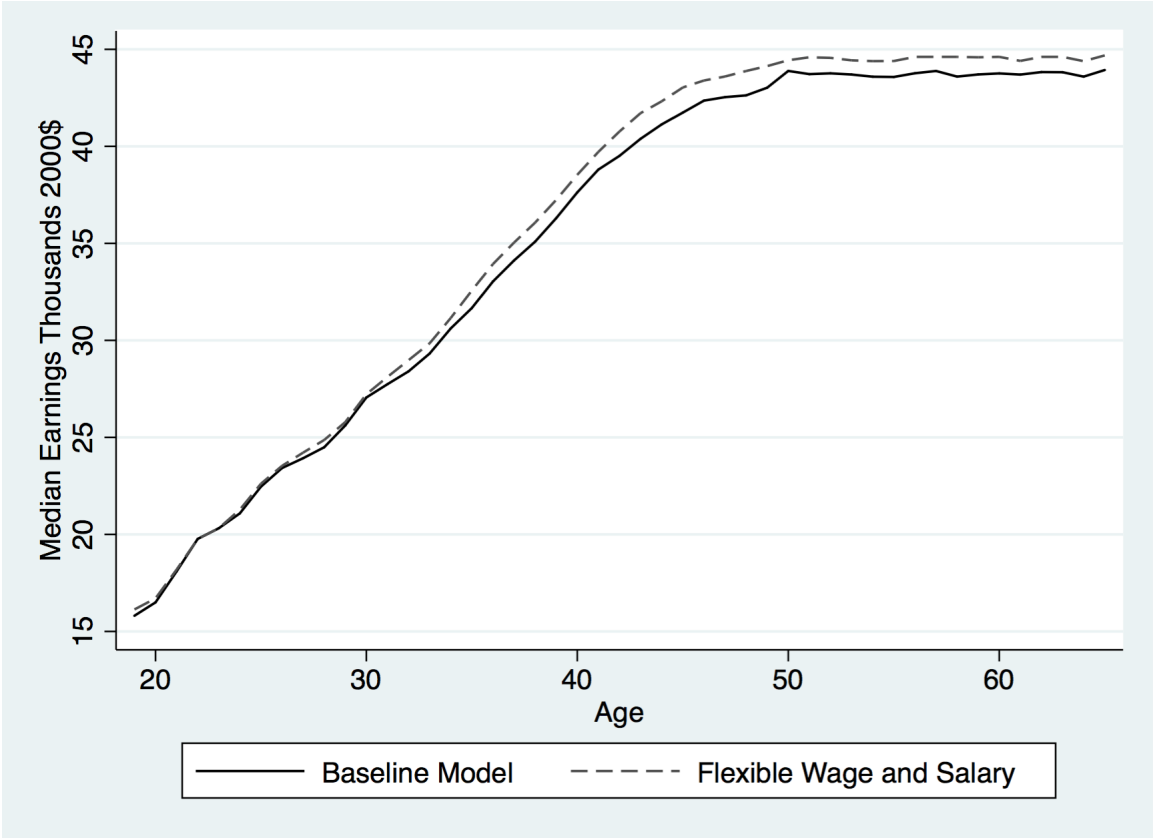
Notes: Figure shows the density of lifetime earnings in the baseline model and the inflexible self-employment counterfactual.

Figure 6. Median Earnings Over the Life Cycle Among Employed Women: Baseline and Inflexible Self-Employment



Notes: Figure shows women's median earnings by age for employed women in the baseline and when self-employment was made inflexible.

Figure 7. Median Earnings Over the Life Cycle Among Employed Women: Baseline and Flexible Wage and Salary Employment



Notes: Figure shows women's median earnings by age for employed women in the baseline and when wage and salary employment was made flexible.

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A Appendix Tables and Figures

Table A1. Second Stage Parameters and Identifying Variation

Parameter	Description	Main Source of Identifying Variation
	Utility Parameters	
β_1^{ws}	Marginal Utility Consumption Wage and Salary Employment	Differences in wage and salary employment rates by similar women with different earning spouses.
β_1^{se}	Marginal Utility Consumption Self-Employment	Differences in self-employment rates by similar women with different earning spouses.
β_2^{ws}	Cost Wage and Salary Employment	Conditional on earnings; identified by the overall share of women selecting wage and salary employment relative to non-employment
β_2^{se}	Cost Self-Employment	Conditional on earnings; identified by the overall share of women selecting self-employment relative to non-employment.
β_3^{ws}	Cost Wage and Salary Employment Associated with Youngest Child 0-5	Identified by differences in wage and salary employment rates between similar women with a youngest child aged 0-5 and those without a child under 10 years of age.
β_3^{se}	Cost Self-Employment Associated with Youngest Child 0-5	Identified by differences in self-employment rates between similar women with a youngest child aged 0-5 and those without a child under 10 years of age.
β_4^{ws}	Cost of Wage and Salary Employment Associated with Youngest Child 6-9	Identified by differences in wage and salary employment rates between similar women with a youngest child aged 6-9 and those without a child under 10 years of age.
β_4^{se}	Cost of Self-Employment Associated with Youngest Child 6-9	Identified by differences in self-employment rates between similar women with a youngest child aged 6-9 and those without a child under 10 years of age.
β_5^{se}	Entry Cost of Self-Employment	Identified by fraction ever becoming self-employed.
β_6	Linear Term Utility Children	Identified by distribution of number of children
β_7	Quadratic Term Utility Children	Identified by distribution of number of children
ρ	Measure of Variance of epsilon	Identified by extent to which observed decisions differ from predictions from the model net of epsilon shocks.
	Earnings Parameters	
γ_0	Intercept	Identified by average earnings in data
γ_1	Unemployment	Identified by differences in earnings of similar women in years with different economic conditions
$f(D_t^{ws}, D_t^{se}, D_t^{ne})$	Piece-wise Linear Terms for Experience Levels	Identified by differences in earnings across similar women with different experience levels
$\boldsymbol{\gamma}$	Education	Identified by average differences in earnings for women with similar experience levels but different education
	Type Specific Parameters	
β_6^k	Linear Term Utility Children	Differences across types are identified by the distribution of the number of children conditional on the opportunity cost of children for that type.
β_7^k	Quadratic Term Utility Children	Differences across types are identified by the distribution of the number of children conditional on the opportunity cost of children for that type.
γ_0^k	Earnings Intercept	Differences across types are identified by differences in average earnings and choices persistent over time for an individual.

Table A2. Top Occupations Among Self-Employed Women Over Time

All Women

1980		1990		2000		2012	
Managers	10.4	Child Care Worker	12.5	Child Care Workers	11.8	Child Care Workers	7.7
Hairdressers	9.3	Hairdresser	7.1	Hairdressers	6.6	Hairdressers	6.5
Sales Supervisors	7.5	Sales Supervisor	5.7	Housekeepers	5.7	Housekeepers	4.9
Child Care Workers	6.4	Managers	4.5	Sales Supervisors	4.5	Real Estate Agents	4.8
Farmers	5.8	Bookkeepers	4.3	Real Estate Agents	3.4	Secretaries	4.1
Bookkeepers	5.3	Farmers	4.0	Bookkeepers	3.1	Sales Supervisor	4.0
Real Estate Agents	3.8	Real Estate Agents	4.0	Salesperson	2.9	Bookkeepers	3.1
Secretaries	3.5	Secretaries	3.1	Secretaries	2.7	Managers	2.7
Other Teachers	3.4	Salesperson	2.7	Farmers and Ranchers	2.7	Designers	2.5
Salesperson	3.1	Designers	2.5	Designers	2.4	Other Teachers	2.5
Door to Door Sales	2.6	Janitors	2.5	Other Teachers	2.0	Salesperson	2.2
Designers	2.0	Other Teachers	2.2	Accountants	1.6	Accountants	2.0
	63.1		55.1		49.5		46.9

Women with Bachelor's Degree

1980		1990		2000		2012	
Other Teachers	8.8	Managers	5.6	Lawyers	4.7	Real Estate Agents	5.4
Physicians	8.3	Other Teachers	5.3	Other Teachers	4.4	Other Teachers	4.9
Managers	6.9	Real Estate Agents	5.1	Designers	4.2	Designers	4.0
Lawyers	6.9	Sales Supervisors	5.1	Real Estate Agents	4.0	Accountants	4.0
Psychologists	5.3	Child Care Workers	4.4	Sales Supervisors	3.9	Lawyers	3.9
Sales Supervisors	4.3	Designers	4.3	Child Care Workers	3.9	Sales Supervisor	3.5
Artists	3.9	Lawyers	3.9	Accountants	3.7	Management Analysts	3.3
Real Estate Agents	3.8	Psychologists	3.6	Management Analysts	3.4	Physicians/Surgeons	3.2
Authors	3.6	Physicians	3.5	Psychologists	3.0	Managers	3.1
Designers	2.9	Artists	3.0	Physicians and Surgeons	2.9	Child Care Workers	3.1
Farmers	2.0	Accountants	2.9	Writers and Authors	2.6	Psychologists	2.7
Management Analysts	2.0	Bookkeepers	2.6	Salesperson	2.5	Secretaries	2.1
	58.7		49.2		43.0		43.2

Notes: 1980, 1990, and 2000 data come from the Census 5% sample and 2012 data come from the ACS. Data were downloaded from IPUMS and estimates include all self-employed women ages 18-65 and are weighted using person weights.

Table A3. Always Married Versus Divorced Individuals

	Always Married	**Divorced**	**P-Value Equality**
Age	35.5	33.0	0.000
Age at Marriage	25.0	22.0	0.000
Number of Kids	1.38	1.19	0.000
High School or Less	40.4	53.4	0.000
Some College	23.0	25.0	0.336
Bachelor's Degree	34.3	19.7	0.000
Person-Year Observations	23,839	12,161	
Choices			
Wage and Salary No Birth	62.3	61.7	0.264
Wage and Salary Birth	3.7	3.4	0.207
Self-Employment No Birth	6.0	5.7	0.219
Self-Employment Birth	0.4	0.4	0.418
Not Employed No Birth	23.8	24.6	0.086
Not Employed Birth	3.8	4.2	0.049

Notes: Column 2 shows summary statistics for the estimation sample, which includes women who are always married. Column 3 shows the same statistics for women who divorce in the data for the years in which they are married. Column 4 provides the p-value for a test of equality of means.

Table A4. Weekly Child Care Expenditures; Positive Payment and Weekly Amount

Variables	**Marginal Effects Probability of Payment**	**Conditional Expenditure (2000$)**
Youngest Child 0-1	0.391**	50.63**
	(0.009)	(1.526)
Youngest Child 2-5	0.3967**	35.69**
	(0.0075)	(1.292)
2 Children	-0.0377**	15.20**
	(0.0073)	(1.004)
3 Children	-0.113**	8.534**
	(0.0092)	(1.647)
4+ Children	-0.153**	8.358**
	(0.0115)	(2.166)
Self-Employed	-0.2516**	-5.861*
	((0.0110)	2.601)
Mother's Age	0.0287**	4.436**
	(0.0043)	(0.662)
Mother's Age Squared	-0.00004**	-0.0538**
	(0.00006)	(0.0101)
Some College	0.0454**	7.390**
	(0.0075)	(0.0101)
Bachelor's Degree	0.1279**	24.50**
	(0.00795)	(1.264)
Year Since 1985	-0.006**	1.748**
	(0.0004)	(0.0918)
Constant		-68.04**
		(10.61)
N	42,463	16,923
R^2		0.156

Notes: Column 1 shows the marginal effects evaluated at the mean values of the independent variables from a probit where the dependent variable is an indicator for positive child care expenditures. The dependent variable in column 2 is the total weekly expenditure on child care services. Data are from SIPP panels 1984-2008. The sample includes employed married women living with at least one child under 10. Standard errors are clustered at the individual level and *p<0.05, **p<0.01

Table A5. Husband's Log Income (2000$); Predicted by Wife's Characteristics

	Estimate	**Standard Error**
Linear Spline in Age		
18-24	0.0559*	(0.0110)
25-29	0.0380*	(0.0063)
30-34	0.0120*	(0.0064)
35-39	0.0210*	(0.0066)
40 Plus	0.0004	(0.0046)
Linear Spline in Age X College Educated		
18-24	-0.0541	(0.0412)
25-29	0.0399*	(0.0165)
30-34	0.0322*	(0.0117)
35-39	-0.0032	(0.0105)
40 Plus	0.0187*	(0.0080)
Unemployment Rate	-0.0321*	(0.0051)
N	14,376	
R^2	0.59	

Notes: Dependent variable is the log of husband's annual earnings; independent variables are characteristics of the wife. Regressions include individual fixed effects. Sample includes women from the NLSY79 who are never observed to be divorced during the sample period. Only estimation years are included in the regression and standard errors are clustered at the individual level. *p<0.05

Table A6. Log Earnings Residuals and Children by Employment Type

	Residuals (Data-Predicted)
Youngest Child 0-5	-0.197*
	(0.028)
Youngest Child 6-9	-0.162*
	(0.029)
Youngest Child 0-5	-0.120
***Self-Employed**	(0.118)
Youngest Child 6-9	0.147
***Self-Employed**	(0.154)
Self-Employed	-0.034
	(0.089)

Notes: Regression to investigate systematic mis-predictions of earnings by presence of youngest child and employment type. I regress indicators for having a youngest child in each age category and interactions with self-employment status on the residuals from the log earnings predictions from the model. Standard errors are clustered at the individual level.

B Appendix B: Data

B.1 NLSY79 Dataset Construction

Sample Creation

The original sampling design included a nationally representative sample, an oversample of minorities, and a military sample. My analysis includes non-Black, non-Hispanic women from the nationally representative sample only. Next, I restrict the sample to women who have observations above the age of 18, after they are no longer enrolled in school and who are observed to marry. I eliminate individuals who have more than one child within a year during the sample, and women who have fewer than five years of data during the estimation period. This sample of 1,795 women makes up the ever married sample of women. My primary sample of always married women, excludes women who are observed to divorce and includes 1,117 women.

Table B1 shows how each sample restriction affects the sample size.

Employment, Fertility, Earnings, Demographic Variable Construction

Education
I used both the highest grade attended and the highest degree attained to assign women into three education categories: high school or less, some college, and a Bachelor's degree or higher. The some college category includes women who received two-year associates degrees as well as those who attended a four-year college but did not receive a degree. I assign the highest education level observed in the survey to each woman for all years of the estimation. Around 24% of my sample re-enroll in school after the estimation begins according to the school enrollment variable, but for 77% of those years the women are characterized as working.

Employment
I use the weekly arrays on labor force status created by the NLSY79 staff to characterize women's weekly activity. For each year, I assign the most common status among the weeks in that year. I consider women who were unemployed or out of the labor force to be not employed. I classify women into self-employment and wage and salary employment according to the job they worked at the longest during that year. Ties are broken by assigning the earliest job.

Earnings
Women's earnings are the sum of their weekly earnings across all of their jobs. I use the hourly wage and usual hours worked to construct weekly earnings for each job. I add up the earnings across weeks to get annual earnings. In years when women are self-employed, I take out the employer portion of the payroll tax to make the pre-tax self-employment earnings comparable to the pre-tax wage and salary earnings. The self-employed have to pay both the employee and employer portion of the payroll tax, while the wage and salary earnings are net of the employer portion.

I winsorize hourly wages above $1,000 per hour and below $1 per hour. This change

affects around 2.5% of person-years, but it might only affect one of the jobs worked at during that year. I winsorize annual hours of work at 5,200 hours, which affects only 0.25% of person-years.

I use information on spousal earnings to estimate a model of husband's earnings. Husband's earnings are the sum of spousal income from wage and salary work and business income in each interview year. The top coding rules for income changed over time in the NLSY yielding vastly different maximum values of income across years. In order to make these measures consistent, I follow Armour et al. (2014) and fit a Pareto distribution to the top 20% of incomes by year and assign the estimated mean of the top coded values to all top coded observations.

Fertility
Using the NLSY79 fertility history on children's birth month and year, I assign children born between January and June of year t to that year and children born between July and December of year t to the following year $t+1$. As previously mentioned, I do not include women in the sample who have more than one child within one year. I do include children born after age 18 but prior to the estimation period. Around 15% of women have children prior to the beginning of estimation so they begin the estimation with children.

Table B1. Effect of Sample Restrictions on Sample Size

	Sample Size
Full NLSY79 Sample Women	6,283
Eliminate Individuals:	
Military Subsample	5,827
Supplementary Subsample	3,108
Black and Hispanic	2,477
No Observations Over 18, Post Schooling	2,443
Never Marry	2,222
Multiple Births in One Year	2,177
Fewer than 5 Estimation Years	1,795
Ever Divorce in Estimation Period	1,117
No Spousal Income Information	1,083

Notes: Data are from the NLSY79.

B.2 SIPP Child Care Expenditure Dataset Construction

Child care expenditure questions have been asked in SIPP topical modules in all panels. See Table B2 for details on which month child care questions were asked across panels. I focus on creating a consistent measure of weekly expenditures on child care for all children. The SIPP asks whether monetary payment is usually made and for families who make a monetary payment the survey asks for the total expenditures for a typical week. If the survey asks about payments for each child individually, I sum up the payments. Child care expenditures

are only available consistently for employed mothers. Additionally, my analysis limits the sample to women with at least one child under the age of 10. Other covariates used from the SIPP include the age of the woman's youngest child, the number of children, her own age, education level and race, the year of the survey and the self-employment status of the mother. Women are considered self-employed if they worked in their own business more hours than they worked at a wage and salary job.

Table B2. SIPP Child Care Data Used

SIPP Panel Year	Wave	Month, Year Interview
1984	5	May 1986
1985	6	Jan 1987
1986	3,6	Jan 1987, Jan 1988
1987	3,6	Jan 1988, Jan 1989
1988	3,6	Jan 1989, Jan 1990
1989	3	Jan 1990
1990	3	Jan 1991
1991	3	Jan 1992
1992	6,9	Jan 1994, Jan 1995
1993	3,6	Jan1994, Jan 1995
1996	4,10	Jul 1997, Jul 1999
2001	4	May 2002
2004	4	May 2005
2008	5,8	Apr 2010, Apr 2011

Notes: Data from these SIPP waves were used to construct the child care models described in Table A4

B.3 Other Data

National level annual unemployment rates come from the Bureau of Labor Statistics. Specifically state unemployment rates are from the local area unemployment statistics database and the national unemployment rates are from the CPS database.