Maternity Leave, Effort Allocation and Post-Motherhood Earnings

Evgenia Dechter*

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Abstract

Women with children earn less than women without children. To study this motherhood wage gap I propose a dynamic model of human capital accumulation in which labor force participation is endogenous and labor supply is measured by hours and effort. Three explanations are evaluated: career interruptions, time and energy demands of child care and selection into motherhood. Empirical decomposition strategy builds on theoretical predictions. The results suggest that loss of human capital is the main reason for mothers' lower wages. Mothers do not reduce their work effort, and there is no evidence that selection drives the motherhood wage gap.

**School of Economics, University of New South Wales, Sydney, NSW, 2052, Australia.* Email: *e.dechter@unsw.edu.au.* I am grateful to Mark Bils for his suggestions. I would also like to thank Sukanya Basu, Rachana Bhatt, Yongsung Chang, Ronni Pavan, Uta Schoenberg and Nese Yildiz for helpful discussions, as well as seminar participants at Bar-Ilan University, Ben Gurion University, EALE 2011, University of Haifa, Hebrew University of Jerusalem, University of New South Wales, SOLE 2011, University of Sydney, Tel Aviv University, University of Rochester and St. Louis FED.

1 Introduction

Motherhood is associated with lower hourly pay. This wage differential, or "family gap", has remained substantial over the decades, and has widened over time, (for review, see Waldfogel, 1998). Most women have children, and strong social and economic pressure persists for mothers, not fathers, to spend more time caring for children.[1] Researchers have documented the motherhood wage penalty to be around 5 to 10 percent per child, whereas the earnings of male workers are positively associated with their number of children, (see for example Lundberg and Rose, 2000). This study presents a new evidence on the origins of this wage differential.

Many studies empirically document the family gap and propose various theories to explain it. Human capital accumulation and depreciation during work interruptions have received much attention in the family gap literature, and in the labor economics literature in general. For example, Altug and Miller (1998) and Cossa, Heckman, and Lochner (2000) find that past work experience significantly affects current earnings. It is also well documented that displaced workers suffer important wage losses, (Jacobson, LaLonde, and Sullivan, 1993), and that job tenure is an important determinant of wage profile (Topel, 1991). In the family gap literature, Hill (1979) finds that controlling for work experience and tenure eliminates the child-related penalty. Her findings contrast with those of Waldfogel (1998), who finds that, even after controlling for education and experience mothers face a 4% wage penalty for one child and a 9% penalty for two or more children. Mincer and Polacheck (1974) and, Light and Ureta (1995) also find that human capital depreciation due to maternity leave plays an important role in explaining the gap but cannot explain it entirely.

Some authors argue that selection into motherhood is the key explanation for the family gap. Korenman and Neumark(1994) and England and Budig (1999) document a negative selection into motherhood, but conclude that unobserved heterogeneity cannot fully explain the family gap. Lundberg and Rose (2001) find that mothers who experience an employment interruption earn lower wages and work fewer hours. However, women who remain continuously attached to the labor force do not experience these declines. Their findings imply that

[1] Around 90% of women have at least one child by the age of 40, (1996 and 2001 Survey of Income and Program Participation).

heterogeneity cannot explain the entire motherhood wage differential.

A third dominant explanation for the family gap follows from the work-effort hypothesis. This theory suggests that lower effort inputs may reduce the productivity of women with children, leading to a lower pay. Becker (1985) develops a framework with time and energy constraints to analyze female and male labor market outcomes. He shows how persons who devote much time to effort-intensive household activities, like childcare, economize on their use of energy at work. Effort is unobserved, but a few studies indirectly test the Becker (1985) theory. Anderson, Binder and Krause (2002) use the age of the child upon the mother's return to the labor market to proxy for energy demands at home, and their findings do not support the work-effort explanation. Phipps, Burton and Lethbrigde (2001) assume that women who spend more time on housework and child care, have less energy for the labor market. They control for time spent on unpaid work and show that the child penalty declines, but remains significant. Waldfogel (1997) argues that if this hypothesis is true, single mothers should have greater effort-related wage penalties, for which no support is found in the data.

A large portion of the family gap literature is directed to examine the effects of mothers' time out of the labor force and decreased working hours on their earnings. These studies commonly implicitly assume that the duration of maternity leave is independent of effort allocation. Here, I develop a dynamic version of Becker's (1985) framework in which human capital is accumulated in a learning-by-doing process, to account for the effects of both work interruptions and energy constraints on post-motherhood earnings. In the setup proposed here, hours worked, effort and maternity leave are determined simultaneously and might be correlated. Following theoretical implications, I propose a decomposition method that accounts for this endogeneity. First, I show that selection into motherhood or into the timing of birth cannot explain the family gap. Next, I examine two explanations of the wage differential: effects of work interruptions on human capital and post-motherhood effort reallocation.

To perform the empirical analysis, I draw from multiple datasets: the 1996 and 2001 Surveys of Income and Program Participation (SIPP) and the 2003 - 2007 American Time Use Surveys (ATUS) and Current Population Surveys (CPS). I construct a first-differences wage specification and compare women who had a child during the survey period to those who did not. For women who had a child I use pre- and post-motherhood wages. I estimate the mean birth-related wage loss to be around 5%. This wage growth differential is decomposed in two steps. First step is to derive human-capital-accumulation process parameters to evaluate the effects of change in human capital on wage growth. In this stage I employ theoretical predictions about the negative trade-off between time and effort allocations: spending fewer hours on an energy-intensive activity allows a person to exert more effort in all activities. A measure of hours worked before and after the maternity leave is used to proxy for a portion of change in effort. To address the remaining heterogeneity, driven by unobservable time and effort demands of childcare, I employ the instrumental variables technique. Observable individual fixed effects are used as instruments. This procedure delivers the average human capital depreciation rate. The net accumulation rate is derived using wage observations of women who were continuously employed and did not have children during the survey period. By constructing the change in human capital for each worker and netting it out from the disparity in wage growth driven by motherhood, I deduce the proportion of wage growth that is due to effort reallocation.

The results show that women who remain on maternity leave and out of the labor force longer tend to earn lower hourly wages when they return to the market. I estimate the monthly depreciation rate of human capital to be around 1%. This coefficient is underestimated in specifications that do not account for the correlation between change in (unobservable) effort and maternity leave duration. The net monthly accumulation rate of human capital is 0.2%. The mean duration of maternity leave is 5.5 months, which implies that the failure to accumulate human capital while on leave explains the entire wage loss experienced by mothers, leaving no room for effort reallocation to explain the gap.

The remainder of the paper is organized as follows. Section 2 builds the theoretical framework, which establishes the relationship between market time and effort, and the origins of correlations between maternity leave and time and effort allocation. It also presents the main empirical implications. Section 3 discusses the data and methods of selecting the key variables. In Section 4, I outline the empirical strategy, discuss the validity of the instruments used in the first stage of the estimations and present the results. Section 5 concludes the paper.

2 The model

This section suggests a dynamic model of the female labor supply in which both time and effort can respond. The model builds on the static time and effort allocation framework, developed in Becker (1985), and expands into a dynamic setup where human capital is accumulated in the learning-by-doing process. Three variables define wages at each stage of the life-cycle: market time, market effort and human capital. Time and effort are chosen every period, and human capital is accumulated by learning-by-doing, and depreciates during time spent out of the labor force.

Time is continuous and the agent lives for T periods and delivers a child at age B. There are no fertility decisions in the model and B is given. The presence of a child is indicated by $x_i(t) = \{0, 1\}$. Utility is defined over streams of consumption, $c(t)$, and effective leisure, $\widetilde{l}(t)$, where $t \in [0, T]$ and denotes the agent's current age. Effective leisure is a function of time, $\widetilde{n}(t)$, and energy, $\widetilde{f}(t)$, devoted to leisure activities, such that $\widetilde{l}(t) = \widetilde{n}(t)\widetilde{f}(t)^{\rho}$. Effective labor on the market $l(t)$ is defined as $l(t) = n(t)f(t)^{\sigma}$, where $n(t)$ and $f(t)$ are time and effort per hour spent on market activities. The parameters ρ and σ are the respective elasticities of effective home and market time with respect to effort exertion, where $0 < \rho$ and $\sigma < 1$. I assume that market work is more energy intensive than housework and leisure activities, which implies $\rho < \sigma$.[2] Each worker is endowed with fixed stocks of time and energy which are allocated over various activities in a single period.

The time constraint is defined as $market\ time + leisure\ time + childcare\ time = 1$. Worker i in period t spends an amount of time $n_i(t)$ in the market and $\widetilde{n_i}(t)$ at home,

$$n_i(t) + \widetilde{n_i}(t) + \eta_i(t)x_i(t) = 1. \tag{1}$$

Workers with children have fewer hours to allocate to leisure and market activities if child care time, η_i, is positive and known at time 0. Individuals may face different time constraints after a child's birth.[3]

[2] This assumption is discussed extensively by Becker (1985) and Bils and Chang (1999).

[3] Heterogeneity in time demands of children might be driven, among others, by the child's health and personality, the parents' experience with children or the parents' philosophy of childcare.

I define $f(t)$ and $\widetilde{f}_i\ (t)$ as the effort levels per hour the worker exerts at work and at home, respectively. The energy constraint takes the following form:

$$n_i(t)f_i(t) + [1 - n_i(t) - \eta_i(t)x_i(t)]\, \widetilde{f}_i(t) + \eta_i(t)\phi_i(t)x_i(t) = 1. \tag{2}$$

This constraint presents workers with a trade-off: working more intensely in the market results in less energy for non-market activities. Energy demands of children per hour are given by ϕ. For simplicity I assume that ϕ is constant. When a child is born, the mother reallocates her time and effort spent on all activities to meet the tightening energy and time constraints.

The agent chooses her consumption stream, $c_i(t)$, time and effort supplies,$n_i(t)$ and $f_i(t)$, and the duration of maternity leave, M_i, to maximize the present discounted value of lifetime utility, given by

$$\begin{aligned} U[c_i(t), \widetilde{l}_i(t), M_i] = & \int_0^T e^{-\theta t} u\left[c_i(t)\right] dt + \int_0^{B_i} e^{-\theta t} v\left[\widetilde{l}_i(t)\right] dt \\ & + \int_{B_i}^{B_i+M_i} e^{-\theta t} v\left[\widetilde{l}_i(t)\right] dt + \int_{B+M}^{T} e^{-\theta t} v\left[\widetilde{l}_i(t)\right] dt, \end{aligned} \tag{3}$$

where $\theta > 0$ and is the rate of time preference. The functions $u(\cdot)$ and $v(\cdot)$ are continuous and twice differentiable with $u\prime(\cdot), v\prime(\cdot) > 0$ and $u''(\cdot), v''(\cdot) < 0$. Three life-cycle stages, before having a child, maternity leave, and after the return to the labor force, are distinguished by discrete jumps in the utility the agent receives from effective leisure, $v\left[\widetilde{l}_i(t)\right]$.

Non-labor income in period t is a sum of assets, $a_i(t)$, and spousal income, $b_i(t)$, where $a_i(0)$ and $b_i(t)\ \forall t$ are exogenous. Given non-labor income, wage $W(t)$, and constant interest rate $r > 0$, the budget constraint for an individual i in period t is given by:

$$a_i(t) + c_i(t) \leq a_i(t-1)(1+r) + b_i(t) + W_i(t) - z_i(t). \tag{4}$$

The wealth constraint is constructed by summing budget constraints over the life cycle.

A worker's wage is a function of working hours, effort level and human capital, formulated as: $W_i(t) = H_i(t)n_i(t)f_i^{\sigma}(t)$. Total worker productivity, $n_i(t)f_i^{\sigma}(t)$, depends on both time and effort, given the elasticity of effective market time with respect to effort exertion, σ, where $\sigma < 1$.

Human capital stock in period t, H_t, equals human capital in the preceding period $H_i(t-1)$ plus the new human capital produced in $t-1$ such that $\dot{H}_i(t) = \alpha p_i(t) H_i(t) - \delta H_i(t)$ and $H_i(0) = H_{i,0}$. The learning-by-doing parameters, δ and α, are the depreciation and accumulation rates, respectively, and, $p_i(t)$ is the indicator of labor market participation, $p_i(t) = 1$ if $n_i(t) > 0$ and $p_i(t) = 0$ otherwise.

The log of observed hourly wages, $w_{it} = \frac{W_{it}}{n_{it}}$, of agent i is given by $\ln w_{it} = \sigma \ln f_{it} + \ln H_{it} + \upsilon_{it}$, where υ_{it} summarizes the measurement error in the data.

2.1 Empirical Specification

Using the wage and human capital specifications, I construct a difference-in-differences equation to evaluate wage rate losses associated with motherhood:

$$\ln w_{it} - \ln w_{i,t-M_i} = \sigma(\ln f_{it} - \ln f_{i,t-M_i}) + (\alpha - \delta)M - \alpha(1 - P_{i,M})M + (\ln \upsilon_{it} - \ln \upsilon_{i,t-M_i}), \quad (5)$$

where M is the maternity leave measure of new mothers, or an arbitrary spell for non-mothers.[4] $P_{i,M} = 0$ indicates that the worker was on maternity leave for M periods.

Equation (5) formulates the wage change using wage observations before and after maternity leave. The first term summarizes the effect of effort reallocation. The interaction between maternity leave and birth indicator (the third term in the equation) sums the wage losses associated with forgone human capital accumulation while out of the labor force. Equation (5) can be used to evaluate the effects of change in effort and human capital on earnings. However, if effort is not observed and correlated with the maternity leave duration, the estimation results might be biased.

Theoretical analysis of shows that the duration of maternity leave, hourly market effort

[4] Lagging human capital for D periods yields the following expressions:

$$\begin{cases} \ln w_{it} = \sigma \ln f_{it} + \ln H_{i,t-D} + (\alpha - \delta)D + \upsilon_{it}, & if\ P_{i,D} = 1, \\ \ln w_{it} = \sigma \ln f_{it} + \ln H_{i,t-D} - \delta D + \upsilon_{it}, & if\ P_{i,D} = 0, \end{cases}$$

where $P_{i,D}$ indicates whether worker i was employed during the D periods and $P_{i,D} = 0$ otherwise.

and the change in market effort, are driven by the same forces and are implicit functions of the marginal utility of wealth, η, H_0 and B. Therefore, the optimal duration of maternity leave, M, and the change in exerted effort at work, $\frac{f_M}{f_0}$, might be correlated.[5] If time demands of motherhood are more important than energy demands, workers with children conserve on time away from home by decreasing their hours worked in the market and increasing their effort inputs. Alternatively, both time and effort inputs may decrease upon the return to the labor force if energy demands of children are relatively high.

The estimation is performed in two steps. First, I use theoretical predictions about the trade-off between effort and hours of work to substitute for the change in effort in equation (5). Second, instrumental variables are employed to address the remaining endogeneity.

To supply effective labor to the market workers choose the number of hours to work and the effort to exert per hour. In this setup, the more hours the worker wishes to supply to the energy-intensive activity - market work, the less effort she will be able to supply to that activity. This relationship between effort exerted at work and hours supplied is derived from the hours and effort first order conditions and the energy constraint. The change in market effort after work interruption can be expressed as a function of hours supplied before and after the child's birth:

$$\frac{f_{i,M}}{fi_{,0}} = (1 - x_{i,M}\eta_i\phi)\frac{n_{i,0}\,(\Gamma - 1) + 1}{n_{i,M}\,(\Gamma - 1) + (1 - x_{i,M}\eta_i)}, \tag{6}$$

where $\Gamma = \frac{\sigma}{\rho}\frac{1-\rho}{1-\sigma} = \frac{f_{i,t}}{\widetilde{f}_{i,t}}$, f_0 is the hourly effort before the work interruption (i.e., a childbirth) and f_M represents effort exerted upon the return to the labor force (M periods later), where $x_M \in [0, 1]$ and indicates the presence of children in period M.

Substituting change in effort from equation (6) into equation (5), and setting $P_M = 0$ and $x_M = 1$ yields the new-mothers' wage change,

$$\triangle \ln w_i = \sigma \ln \left[\frac{n_{i,0}\,(\Gamma - 1) + 1}{n_{i,M}\,(\Gamma - 1) + (1 - \eta_i)}\right] - \delta M_i + \sigma \ln(1 - \eta_i\phi) + \triangle\upsilon_i. \tag{7}$$

Parameter Γ is the ratio between energy inputs at work and at home. It was calibrated by Bils

[5]Theoretical analysis and proofs are available from the author upon request.

and Chang (1999) and is set at $\frac{3}{2}$. Bils and Chang calibrate Γ using information from Passmore, et al. (1974) who document energy expenditures (in calories) for work in various occupations and for a range of leisure activities. I also use alternative values of Γ for sensitivity analysis.

If all variables in equation (7) are observed, a simple OLS procedure will provide unbiased parameter estimates. However, the coefficients might be biased if the time demands of children, η_i, are unobserved and correlated with the duration of maternity leave and time reallocation decisions. I resolve the endogeneity and non-linearity issues using a Two-Sample TSLS (TSTSLS).[6] TSTSLS can be implemented if two datasets share a common set of instruments but the endogenous regressors and the dependent variable are not jointly included in both datasets. In the current context, the first-stage regression of the first term in equation (7), $\ln\left[\frac{n_{i,0}(\Gamma-1)+1}{n_{i,M}(\Gamma-1)+(1-\eta_i)}\right]$, is estimated using data from the combined sample of the American Time Use Survey and Current Population Survey (ATUS-CPS; 2003 - 2007). This data set includes measures of hours, time spent on child care and the set of instruments but does not contain a measure of maternity leave. To proxy for η I use a measure of time spent on physical child care (i.e., feeding, medical care, grooming). A detailed description of the data is provided in the following section.

I estimate the first stage of the maternity leave decision and the second-stage equations using the main dataset, Survey of Income and Program Participation (SIPP; 1996, 2001), from which all variables in equation (7) except η and ϕ are available. The vector of instruments, Z, contains the same set of variables in all first stage specifications. The choice of the instruments is driven by theoretical specifications of the time allocation and maternity leave decisions. The lifetime budget constraint implicitly determines the optimal value of the marginal utility of wealth, which affects both maternity leave and time allocation decisions. Marginal utility of wealth is a function of initial assets, lifetime wages, fixed costs of work, interest rates, rates of time preference, consumer tastes, initial human capital level, age at the child's birth and time and energy demands of children. Variables in this set that are not correlated with the time demands of children can be used as instruments for maternity leave and hours worked.

Using the proposed estimation strategy, I employ equation (7) and estimate the depreci-

[6]For more details about the method see Angrist and Krueger (1992).

ation rate, δ. I estimate the net accumulation rate, $\alpha - \delta$, using a subsample of women who did not have a child during the survey period. With α and δ in hand, I net out the effects of the change in human capital on wage growth and evaluate the remaining possible source of the difference between new mothers and non-mothers, effort reallocation.

3 Data

Survey of Income and Program Participation (SIPP)

I examine the main implications of the model using panel data from the 1996 and 2001 Surveys of Income and Program Participation (SIPP). The SIPP features a panel structure and collects detailed monthly demographic and employment activity data for all persons in the household for each interview reference period (a wave). The 1996 SIPP Panel was conducted for 12 waves, collecting data for a continuous 48-month period. The 2001 survey consists of 9 waves and has observations for 36 months. Some information was obtained for each month in the four-month reference period; in other cases, information is available once per wave. The survey includes questions on a wide range of topics, including family background, education, fertility and work histories, child care arrangements, assets and earnings for all household members.

To study the effects of childbirth on female labor market outcomes, I restrict the sample to married couples only, in which the wife is between the ages of 18 and 45. Individuals must not be in the armed forces, disabled or attending school full time. Also, I do not use observations that are missing any key variables (e.g., hours, earnings, age, education). The raw sample used in this study contains information on 20,707 women (and their spouses), 3,736 of whom had a child during the course of the panel. New-mothers with at least one wage observation before and after birth account for 1,252 cases. "Non-mothers" with continuous wage observations provide 4,610 observations.[7]

The dependent variable in most of the analyses is the change in log real hourly wage rate

[7] I use the term "new mothers" to refer to women who gave birth during the survey period. The last child is the relevant one for analysis purposes. "New mothers" may have previous children. The control group, "non-mothers" is constructed using observations of women who did not have a child during the survey. These women also may have children who were born before the survey period.

for the main job (in 2000 US dollars). To calculate the change, I use averages of the wage before and after the maternity leave. I use wages reported from 12 to 3 months prior to child's birth to construct the "before" measure. Wages observed 1 to 12 months after the return from maternity leave are used to obtain the average "after" wage.[8] I consider a wage change as unreasonable if the hourly wage increases by more than 400%, or decreases by more than 75% while on leave (about 25 observations).

Summary statistics of the variables used in this paper are given in Table 1. Women who delivered a child are fairly similar to women in the control group in terms of education, race, and labor force outcomes before childbirth. Their hours worked and wage rate after return to the labor force are significantly lower than those of women who worked continuously and did not have children. Women who did not have a child during the survey period are older (by 5 years on average) and have more children (0.5 more, on average).

The maternity leave variable measures the number of non-working months immediately following a birth, unless the leave have started before the birth. Respondents report their labor market status for each week during the survey month. A leave that started before and up to three months after the birth date is considered valid. Once the new-mother is observed to be working, her maternity leave is considered to be concluded. The maternity leave measure is limited because SIPP tracks only unpaid leave. Thus, if paid leave was not followed by some period of unpaid leave, leave duration will be recorded as zero months; using this definition, 25% of new-mothers have zero maternity leave. This 25% figure can be compared to the 4% of zero leaves reported in the second wave of1996 panel; this wave records the actual length of paid or unpaid maternity leave taken after giving birth to first child. For women who have zero leave, I take a few more steps. First, I update the maternity leave measure using other available labor status variables: monthly employment status, hours worked, monthly earnings. Second, during the second wave of the 1996 survey, female respondents were asked about their fertility history and reported the length of maternity leave taken after their first birth. For women with zero months of leave who remained with the same employer since birth of their first child, I

[8] I do not include the last two months in the measure of hours worked before childbirth since some women change their work schedule significantly in the final months of pregnancy. Additionally, to construct the "after" wage I use observations collected during the waves started after return to the labor force.

correct the duration of leave to the duration reported in the second wave. These two procedures reduce the percentage of workers with zero months of leave to 20%. Additionally, employees who reside in California, Hawaii, New Jersey, New York or Rhode Island and railroad industry employees are entitled to at least 6 weeks of paid leave provided by Temporary Disability Insurance (TDI). For these women, I correct the maternity leave period from zero months to the shortest period offered by law in these states, 1.5 months.[9] This correction reduces the fraction of women taking zero months maternity leave to 15%. The distribution of the duration of maternity leave among women who worked prior to having a child is given in Figure 1. The mean duration of maternity leave is measured at 5.4 months, given in Table 1. The potential measurement errors in the maternity leave variables are considered in the empirical analysis. Additionally, I repeat some estimations using only non-zero maternity leave durations, but do not obtain different results.

For comparisons between new-mothers and non-mothers I construct a "leave" for the latter group as well. For non-mothers, it is a random variable drawn from the percentage distribution of maternity leave provided in the second wave of SIPP 1996.

American Time Use Data (ATUS) and Current Population Survey (CPS)

SIPP data provide no information about time spent caring for children. Therefore, first-stage estimations and validity tests of the instrumental variables that require information on the time demands of children cannot be performed using the SIPP. I use data from the 2003-2007 waves of the American Time Use Survey (ATUS) merged with Current Population Surveys (CPS). ATUS data contains measures of time spent with children. Merging ATUS with CPS allows to measure both the change in working hours around birth and time spent caring for the newborn.

ATUS uses a 24-hour recall of the previous day's activities. Within each households that participates in ATUS, one randomly selected member (age 15 and up) was asked to provide information about his/her daily activities over a randomly assigned 24 hour period. Respondents were asked to describe each activity they did that day, and how much time (in minutes) they spent on the activity. Each day of the week is equally represented within the survey, and

[9]Generally, employers that provide TDI, must cover pregnancy and childbirth as well.

I use only information collected on weekdays and non-holidays. The raw ATUS data contains 72,922 observations. My primary analysis sample includes married women between the ages of 18 and 45 who worked on the diary day and spent some time providing child care. Because it is impossible to specify which child in the household received care, I specify a subsample in which I include only respondents with one child under two years old (for compatibility with the SIPP sample). This subsample counts 393 observations of mothers. (Married women with one child below 5 years old account for 499 observations)

The analysis uses two definitions of child care. "Physical child care" is any time spent meeting the basic needs of children, including breast-feeding, rocking a child to sleep, general feeding, changing diapers, providing medical care, grooming, etc. This variable proxies for time demands of children. “Non-physical child care" includes time spent on education (e.g., reading to children, teaching children or attending meetings at a day care center) and on recreational child care (e.g., playing games with children, playing outdoors with children, going to a zoo or taking walks with children). Table 2 shows summary statistics for the ATUS sample.

To obtain information about pre-birth labor market activity I match previous waves of CPS data with a subsample of 2003 - 2007 ATUS. Because questions about usual weekly hours and earning are asked only in the 4th and 8th interviews, the ATUS subsample is merged with observations collected during outgoing rotations of CPS. Following Madrian and Lefgren (1999), individuals are identified in the panel data not only by their ID number but also by matching a set of time-invariant characteristics. Around 75% of the 393 observations in the ATUS subsample could be matched with previous CPS waves, of those 150 respondents had a child during the CPS course and had wage and hours observations prior to having their first child. Due to the low number of observations in some specifications weekend data is utilized as well, which increases the merged ATUS-CPS sample to 277 observations. Descriptive statistics for these data are given in Table 2.

The statistics presented in Table 2 show that the average time spent on physical child care is around 1.4 hours per day, in both subsamples, ATUS-CPS and ATUS. Statistics of age, education, spousal education and metro status, are fairly similar to those obtained using the SIPP data.

4 Empirical Analysis

Having established a framework where allocations of market time and effort and the duration of maternity leave are endogenous, I examine the origins of childbirth-related wage loss. I also discuss the limitations of the standard family gap estimations. Correlation between maternity leave duration and effort reallocation decisions may lead to a biased decomposition of the motherhood wage penalty. The effects of selection into motherhood on wages are assessed separately by comparing wage rates of future mothers to those of women who will not have children in the near future. I find no indication of selection.

4.1 Family Gap Estimations

Log wage rates before and after maternity leave, or an arbitrary spell, are given by

$$\ln w_{it-M} = \sigma \ln f_{it-M} + \ln H_{it-M} + \upsilon_{it-M}, \tag{8}$$

$$\ln w_{it} = \sigma \ln f_{it} + \ln H_{it-M} + (\alpha - \delta)M - \alpha(1 - P_M)M + \upsilon_{it}, \tag{9}$$

where P_M is an indicator of having a child and M is the maternity leave, or an arbitrary time period for non-mothers. In practice, the total family gap can be estimated using a form of equation (10):

$$\ln w_{it} = \beta Birth + \ln H_{it-M} + \upsilon_{it}, \tag{10}$$

where $Birth \in \{0, 1\}$ and β summarizes the average of $((\alpha - \delta)M - \alpha BirthM + \sigma\Delta \ln f_{it})$ and the differences in unobservable characteristics if mothers were a selected group. The control group in this specification, women with $Birth = 0$, includes only continuously employed non-mothers. Estimating equation (10) represents the common approach to assess the effects of motherhood on wage, where $Birth$ may replaced by a vector of dummy variables to summarize the number of children in the household.

Subtracting equation (8) from equation (9) nets out individual fixed effects. The first differences equation of the hourly pay rate between periods t and $t - M_i$ is given by equation (5) and takes the form:

$$\Delta \ln w_{it} = \sigma \Delta \ln f_{it} + (\alpha - \delta)M - \alpha BirthM + \Delta \upsilon_{it},$$

When summarizing all unobservables using a dummy variable to indicate birth, (or using a vector of dummy variables to indicate the number of children), equation (5) takes the following form:

$$\Delta \ln w_{it} = \beta Birth + \Delta \psi_{it_i}, \tag{11}$$

where β summarizes the average of $((\alpha - \delta)M - \alpha BirthM + \sigma \Delta \ln f_{it})$. This equation is comparable to fixed effects models used in earlier studies that evaluate the family gap.

I first estimate equations (10) and (11) and compare the results to those of previous studies.[10] Table 3 displays the results. Column (1) of Table 3 provides estimates of equation (11). The coefficient of the $Birth$ variable in this regression is -4.9% and corresponds to the mean wage loss due to motherhood. Column (2) displays estimation results of equation (10). The coefficient of the $Birth$ indicator is -4.2% in this specification, showing no support for the hypothesis of negative selection into motherhood. The estimated coefficients of the future birth on wage growth and wage level, in columns (3) and (4), respectively, also suggest that, controlling for observable characteristics, there is no negative selection into birth timing or motherhood. Women who will have children in the near future do not earn less and do not have lower wage growth compared to those who will not. The effects of birth on hours worked before and after are given in columns (6) and (7).[11] Childbirth has a strong negative effect (-13%) on hours worked after the return to the labor force, but the data show no significant negative effect of future birth on hours worked before the pregnancy.

The estimated -4.9% family gap in the first difference specification is comparable to estimates reported in other studies. For example, using fixed-effects models, Anderson, Binder and Krause (2002) find this gap to be around 3%, and Waldfogel (1997) estimates 6%. In a

[10] In these estimations education, age, race, metro status and number of children are used as control variables.

[11] To construct a measure of hours worked before for new mothers I use only pre-pregnancy observations (12 to 18 months before the birth).

cross-sectional analysis, Anderson et al. (2002) and Waldfogel (1997) find the wage penalty for one child to be 4% to 7%.

4.2 Step I: Estimating the Depreciation Rate of Human Capital

The estimation results in Table 3 suggest the family gap is not driven by selection, when age, education and other characteristics are taken into account. The next step is to quantify the wage losses associated with motherhood into depreciation of human capital and effort reallocation. Motherhood wage penalty is decomposed in two steps. First, I obtain the human-capital-accumulation process parameters to evaluate the effects of work interruptions on wage rates. I estimate the depreciation rate of human capital using the subsample of women who gave birth during the survey period. Net accumulation rate is derived using a subsample of women who were continuously employed and did not have children during the survey course. The final step is to derive the proportion of the wage growth that is due to effort reallocation.

Wage losses of new-mothers are given in equation (7), the following equation is estimated:

$$\triangle \ln w_{it} = \sigma \ln \left[\frac{n_0 \left(\frac{2}{3} - 1\right) + 1}{n_M \left(\frac{2}{3} - 1\right) + (1 - \eta)} \right] - \delta M + \sigma \ln(1 - \eta\phi) + \beta X_{it} + \triangle \upsilon_i, \qquad (12)$$

where X_{it} is a set of control variables and includes race, age, number of prior children, metro status and spousal working hours.

The key parameter of interest in equation (12) is the monthly depreciation rate, δ. The coefficient of maternity leave in (12) may also summarize effects of changing job characteristics. For example, women who stay longer on leave may also be more likely to switch to jobs that offer better hours flexibility but lower pay. In this case δ will not only reflect the depreciation rate but also changing work conditions. To evaluate this interpretation I estimate equation (12) for job stayers only and show that results are very similar to those obtained for the full sample.

An OLS procedure will provide a consistent estimate of δ only if there is no variation in the unobservable time and effort demands of children. However, if there is such heterogeneity, estimated coefficients might be biased. The TSTSLS procedure addresses these heterogeneity issues. I choose instruments from the set of individual fixed effects variables: education, spousal education, non-labor and spousal income and a state policy indicator of whether paid maternity leave (TDI) is available. Different combinations of instruments are used for robustness tests. The choice of instruments is derived from theoretical implications, where these variables determine the marginal utility of wealth, and therefore affect labor market choices. From the empirical perspective, these variables are not correlated by construction with the change in the individual specific error component, $\triangle\upsilon_i$. I also test for orthogonality between the instruments and $\sigma\ln(1-\eta\phi)$. Additionally, a set of alternative instruments, total net worth record and state dummy variables, is used to examine the robustness of the coefficients. The instrumental variables approach should also correct any biases associated with classical measurement error in the maternity leave variable and hours of work.

4.2.1 First-Stage Results

To proxy for the time demands of children, η_i, I use the measure of time spent on physical child care, (e.g., feeding, rocking a child to sleep, changing diapers, providing medical care and grooming).[12]

The first step is to estimate the function of change in hours using the ATUS-CPS merged data where the time demands of children are observable. The equation is specified as

$$\ln\left[\frac{n_0(\Gamma-1)+1}{n_m(\Gamma-1)+1-\eta_i}\right]=Z_i\gamma^n+X_{it}\theta^n+\xi^n, \tag{13}$$

where Z_i is the vector of instruments, including education, spousal education, spousal income, spousal income squared and a state maternity leave policy indicator. X_i includes race, age, number of children before the current birth,[13] metro status and spousal working hours.

Then, I estimate the maternity leave equation by using the SIPP data:

$$M_i=Z_i\gamma^M+X_{it}\theta^M+\xi_i^M. \tag{14}$$

[12] I assume that the activities on this list are either directed by the child's needs or by parental beliefs about child care.

[13] ATUS data provides measures of time spent on child care of all children in the household. Because it is almost impossible to distinguish between the amount of care received by each child, I limit ATUS estimations to households with one child who was born during the 16 - 20 months of the CPS and ATUS surveys.

Note that the vectors Z_i and X_i contain the same sets of variables in all estimations.

I implement this two-stage procedure due to data availability: $\triangle \ln w_i$, Z_i, X_i, n_0 and n_M are present in both datasets, whereas M is available only in SIPP and η_i is available only in ATUS. The standard errors of the structural coefficients are corrected for the fact that a predicted variable is used in the second stage.

Table 4 displays the first stage estimation results. The estimates in column (1) show a strong relationship between the change in hours worked and spousal income. This relationship is non-linear and implies that spousal income is negatively correlated with change in hours at lower spousal income levels and positively at higher spousal incomes. Column (2) displays similar outcomes for a larger sample that includes weekends. Columns (3) and (4) use $\ln\left[\frac{n_0(\Gamma-1)+1}{n_m(\Gamma-1)+(1-\overline{\eta})}\right]$ to proxy for $\ln\left[\frac{n_0(\Gamma-1)+1}{n_m(\Gamma-1)+1-\eta_i}\right]$. This exercise allows to evaluate the deviations from the true coefficients if the first-stage equations were estimated using the SIPP data, which does not provide a measure of the time demands of children. The results in columns (3) and (4), using workdays and all weekdays, differ in magnitude but show similar patterns to those obtained using the information about time spent on child care.

The last two columns of Table 4 show estimates that were obtained using the SIPP data. Column (5) presents the results from regressing the proxy of hours ratio, $\ln\left[\frac{n_0(\Gamma-1)+1}{n_m(\Gamma-1)+(1-\overline{\eta})}\right]$. SIPP and ATUS-CPS provide fairly similar results. I estimate the second stage equations for each first-stage regression.

Column (6) in Table 4 displays the estimation results of the maternity leave equation using the SIPP data. These results are in line with the theoretical analysis. Higher education leads to a shorter leave, whereas higher spousal education prolongs the leave. Spousal income is negatively correlated with maternity leave duration for lower income levels, whereas this correlation is positive for higher spousal incomes.

For specifications estimated using the SIPP data I perform relevance tests. The F-test statistic of excluded instruments for maternity leave regression is 9.3 and 4.6 for the hours ratio regression. The Cragg-Donald weak identification statistic is 5.4, which suggests that the maximum bias of TSLS will be no more than 20% of the bias of OLS.

4.2.2 Validity of the Instruments

Education might be correlated with child care demands if there is a relationship between child care abilities or beliefs about how much time and effort to spend on child care and education. Alternatively, spousal education might be correlated with his degree of participation in child rearing.[14] In most tests data is drawn from ATUS and CPS, 2003 - 2007. I test whether the mother's time spent on child care and parental education are related in families with one child under the age of 2 years. Only individuals who spent some time on physical child care on a given day are in the sample. The outcomes are presented in column (1) of Table 5 and suggest that there is no relationship between education and physical child care. I also regress a measure of time spent on non-physical child care during a given day using similar explanatory variables, these results are in column (4). These estimations provide statistically insignificant coefficients as well but their point estimates have higher absolute values. As an additional robustness check, same estimations are performed for parents of one child below 5 years old, the results are displayed on the lower panel of Table 5. These estimates suggest similar conclusions, i.e. no significant correlation between education and the time demands of children (proxied by physical child care).

I also test whether spousal income and time spent on physical child care are correlated. For example, wealthier workers may employ more child care help, which would lead to a negative correlation between the time demands of children and non-labor income. The results are reported in columns (2) and (5) of Table 5. Coefficients of spousal income in various specifications are not different from zero, especially in estimations that use physical child care and not other child care specifications.

The estimation results in columns (3) and (6) use all available instruments. These results also show that there is no statistically significant relationship between the instruments and the time spent on physical child care and support the assumption about orthogonality between the instruments and $\sigma \ln(1-\eta\phi)$.

Additionally, during the 7th wave of the SIPP, some of the respondents were asked whether

[14] To test the assumptions about orthogonality between the instruments and $\sigma \ln(1-\eta\phi)$, ϕ is set to equal 1. The conclusions do not change if using other values of ϕ, where $\phi \in [1,2]$.

they feel that their children are harder to care for than most children.[15] I evaluate the correlations between this variable and both respondent's education and spousal income. In these estimations, I use only the answers of those respondents who had their first child during the survey course but before Wave 7. The results are reported in Table 6 and suggest that there is no significant correlation between education, spousal income and the hardship of child care.

4.2.3 Results

The OLS results are presented in columns (1) and (2) of Table 7. Column (1) presents the estimates of $\triangle \ln w_{it} = -\delta M_i + X_{it}\beta + \triangle\xi^1_{it}$, where the change in effort enters into the error term. The estimated monthly depreciation rate in this specification is 0.6%. Column (2) shows the results for $\triangle \ln w_{it} = \sigma \ln \left[\frac{n_0(\Gamma-1)+1}{n_M(\Gamma-1)+(1-\overline{\eta})}\right] - \delta M + \beta X_{it} + \triangle\xi^2_{it}$, where $\overline{\eta}$ is the mean value of η_i measured in the ATUS data. The results in column (2) show that the addition of the hours ratio positively affects the estimated depreciation rate, which increases to 0.7%. This outcome implies that the portion of the change in effort that is captured by the proxy of hours ratio is positively correlated with the duration of maternity leave but is relatively small.

TSTSLS estimation results are reported in columns (3) and (4) of Table 7. The difference between columns (3) and (4) is in the data source used in the first-stage estimation of the hours ratio. Monthly depreciation rate estimates obtained in both specifications (using ATUS-CPS or SIPP) are very similar and are in the range of 1.1 - 1.2%.

The depreciation rate measure may also reflect changing work conditions. If women who stay longer on leave also tend to seek jobs with higher hours flexibility then δ reflects not only depreciation but also changing job conditions. Table 8 provides results based on a subsample of job stayers in an attempt to minimize the effects of changing work conditions on estimates. A discussion of these results is given in Section 4.2.4.

Both the OLS and IV results show that the duration of maternity leave has a significant impact on earnings. TSTSLS estimates of the depreciation rates are comparable to those found in the existing literature. Many authors consistently find that displaced US workers face a large and persistent earnings loss upon re-employment in the range of 10% to 25% per year of non-

[15] "My children are much harder to care for than most children. How often do you feel this way?": 1. Never; 2. Sometimes; 3. Often; 4. Very often.

participation, (see for example, Bartel and Borjas, 1981; Ruhm, 1987; Jacobson, LaLonde and Sullivan, 1993; Fallick, 1996). Mincer and Ofek (1980), use panel data and find that one year of non-participation results in 3.3% to 7.6% wage loss in the short run for married women. Mincer and Polachek (1974) find that motherhood-related work interruptions lead to a 4.3% annual wage loss for women with at least some college education, (comparable to the relevant education group outcomes in this study).

The last two columns of Table 7 report results obtained using alternative sets of instruments. In column (5), I use spousal income and net worth to instrument for the proxy of hours ratio and for the maternity leave duration. In column (6), I use state dummy variables as instruments, (state indicators should pick up information about regional labor market conditions, legislation and social norms). The monthly depreciation rates estimated in these specifications are very similar to (but less precise than) those obtained using the other specifications.[16]

Comparison of OLS and IV Estimates If there is a positive relationship between the change in effort and the duration of maternity leave, OLS tends to underestimate the true depreciation rate. In this case, the depreciation rate obtained through OLS will be smaller than a valid TSLS estimate. This result implies that women who choose to stay out of the labor force longer after childbirth will also choose to work shorter hours after returning to work and to exert more effort per hour of work. These allocations are feasible if child care is more time consuming than energy consuming. If this is the case, then a worker who spends fewer hours working in the market is able to allocate more effort to all activities.

A second potential reason for the TSLS estimate to exceed the OLS estimate is that a shorter duration of leave may reflect changes in market conditions. For instance, workers who have better job offers are more likely to return to work earlier. In this case the human capital depreciation rate obtained in OLS estimations is downward biased.

The presence of measurement errors may also yield a downward bias in the OLS estimates. Measurement error in the maternity leave variable may attenuate the OLS estimates, but the IV results are not affected. To evaluate the potential effects of measurement errors, I repeat OLS and TSTSLS estimations using only a subsample of individuals with non-zero entries for

[16]First-stage estimation results for these specifications are available from the author upon request.

maternity leave. The coefficient estimates are not different from those reported in Tables 4 and 7. These results are not reported here but are available upon request.

4.2.4 Robustness Tests

The subsection provides a robustness analysis for human capital depreciation rate.[17]

Human Capital Depreciation and Education There is no consensus on how education affects the motherhood wage penalty. For example, Anderson, Binder and Krause (2002) find that more educated mothers experience larger wage losses, while Amuedo-Dorantes and Kimmel (2003) find that college-educated women experience no penalty. Because the human capital accumulation process might be correlated with education, I estimate TSLS and OLS regressions separately for high school graduates and dropouts and workers with more than a high-school education. The results show that the depreciation rate does not vary much across educational levels.

Human Capital Depreciation and Occupational Choice The analysis presented up until now does not distinguish between general and firm-specific human capital. This distinction might have important economic consequences because workers who spend more time on maternity leave (more than 12 weeks) are not protected by the law and are more likely to start a new job upon their return to the labor force.[18] Additionally, women who spend longer out of the labor force may obtain jobs with different characteristics, for example, with higher hours flexibility but lower pay. This possibility raises the question of whether the results are driven by those workers who change jobs. I find that 28% of new-mothers change jobs, compared to 11% of women in the control group. To address job mobility, I perform OLS and IV estimations using only observations of those who do not switch jobs ("stayers"). The results are reported in Table 8. OLS results are displayed in columns (1) and (2). Depreciation rates in these specifications are 0.6 - 0.7%, very similar to the values obtained using the entire sample. TSTSLS results for stayers displayed in column (3), are not very different from estimates using the en-

[17]Results of all unreported models and tests are available from the author upon request.

[18]Family and Medical Leave Act (FMLA), which entitles most workers to up to 12 weeks of job-protected medical leave for child birth.

tire sample; the point estimate of the monthly depreciation rate is 1.3 percent and significant at 10% level.

I also examine whether human-capital-accumulation parameters differ by occupation or industry. First, I add occupation and industry indicators to the basic OLS and TSLS specifications. I find that this modification does not change the estimated depreciation rates. In addition, I decompose the population of new-mothers by occupational category. For this exercise, I use the most highly represented occupations: professionals and managers, administrative support workers, sales workers and a merged category of laborers and personal and food service workers. For these estimations, I use pre-motherhood occupations. I find that the estimated depreciation rates for the first two categories are slightly higher than those found for the entire sample are. The estimates for the group of workers who were employed in sales positions or in low-skill jobs are lower than those found for the entire population are.

Additionally, I evaluate the effects of occupational choice on net accumulation rate of human capital. These results are reported in Table 10. I perform these estimations using a subsample of continuously employed women who did not give birth during the sample period. I find no significant effect of occupations on net accumulation rate.

Selectivity Adjustment The estimations use observations of wages before and after maternity leave. However, not all new-mothers return to the labor force before the completion of the survey. Truncated spells cannot be used, because data on the new wage are not available. Although the date of a child's birth is random, truncated unemployment spells might be correlated with longer unemployment. To correct for this selection I implement the conventional two-step selectivity adjustment procedure suggested by Heckman (1979).

Selectivity adjusted results are reported in Table 9. In these estimations, I assume that all explanatory variables are exogenous. First, I estimate a probit selection model using all exogenous variables and the month of childbirth. In column (3), I report the results obtained using additional instruments to control for the non-random selection. Selectivity-adjusted estimations show similar patterns to those obtained using the OLS specifications, which implies that the depreciation rate is not different for the truncated observations.

4.3 Step II: Evaluating the Effects of Work Effort Reallocation

At this stage I compare wage changes of new-mothers and non-mothers, before and after netting out the effect of human capital accumulation process. To adjust new-mothers wage growth I add the depreciation of human capital to the wage change. Non-mothers wage growth is corrected by subtracting the net accumulation of human capital. These estimations allow to decompose the wage change differential between new-mothers and non-mothers into two channels: loss of human capital accumulation and mean change in work effort.

To estimate the net accumulation rate $(\alpha - \delta)$, I use a subsample of women who were continuously employed and did not have children during the survey period ($Birth = 0$). I estimate the following equation:

$$\Delta \ln w_{it} = (\alpha - \delta)M + X_{it}\beta + \Delta\upsilon_{it}.$$

The results are reported in Table 10. The monthly human capital net accumulation rate, $(\alpha - \delta)$, is robust across various specifications and is around 0.2%.

To decompose the wage gap, I estimate the following specification:

$$\widehat{\Delta \ln w_{it}} = Birth\left[\sigma \Delta \ln f_{it}\right] + X_{it}\beta + \Delta\upsilon_{it}, \tag{15}$$

where change in wage is corrected by netting out the changes in human capital, $\widehat{\Delta \ln w_{it}} = \Delta \ln w_{it} + \widehat{\delta} M$ if $Birth = 0$ and $\widehat{\Delta \ln w_{it}} = \Delta \ln w_{it} - (\widehat{\alpha - \delta})M$ if $Birth = 1$. I assume that there is no change in the effort allocation of continuously employed non-mothers.

Using equation (15) is used to evaluate new-mothers' mean change in work effort (scaled by the elasticity of effective market time with respect to effort exertion), which is summarized by the coefficient of the childbirth indicator. The difference between the coefficients of $Birth$ in equations (11) and (15) provides an estimate of the mean motherhood wage rate loss driven by the foregone human capital accumulation.

Estimation results of equation (15) are reported in Table 11. Column (1) reports the total wage growth differential between new-mothers and non-mothers; estimated using equation (11), the total motherhood wage penalty is around 5%. The estimation results of equation

(15) are displayed in column (2) of Table 7. The coefficient of the childbirth indicator is not significant, and its point estimate is positive. This result implies that, on average, forgone human capital accumulation while on maternity leave is the key mechanism behind the wage growth gap between new-mothers and women who did not have children during the survey period. The third column of Table 11 reports decomposition results using the OLS estimate of monthly depreciation rate, $\delta = 0.6\%$. In this case almost one third of the maternity wage loss remains unexplained by changes in human capital. The latter result is comparable to findings in the family gap literature. In a model that does not account for the correlation between maternity leave and effort reallocation this unexplained wage loss could be attributed to a reduction in the effort exerted at work.

The decomposition result does not imply that new-mothers do not adjust their effort. The empirical findings suggest that a woman who takes an average maternity leave will resume working with the same level of hourly effort. Moreover, on average, women who take shorter leaves exert lower effort upon their return to work, while women who take longer leaves return with higher work effort.

5 Conclusion

The negative impact of motherhood on individual wages is a well-established empirical fact. The key explanations often found in the family gap literature include effects of career interruptions, energy demands of children and selection into motherhood. The existing literature offers various ways to estimate and decompose the family gap, and the findings tend to support, at least to some extent, all three explanations, though these estimates overlook potential biases generated by the relationship between the energy reallocation decision and the duration of maternity leave.

In this paper I examine the family gap in a dynamic model of human capital accumulation. In the proposed setting labor force participation is endogenous and labor supply is measured by hours and effort. I derive a series of theoretical implications which are used to construct the empirical decomposition strategy.

Empirical estimations are performed in three steps. First, I net out individual fixed effects by constructing a first-differences log wage specification using pre- and post-motherhood wage rates. Second, I estimate the effects of the change in human capital on wage change, these estimations yield measures of depreciation and accumulation rates of human capital. The net accumulation rate is derived using wage observations of women who were continuously employed and did no have children during the survey period. To obtain a consistent measure of human capital depreciation I use a subsample of women who gave birth during the survey period. I control for the correlation between unobservable energy reallocation and maternity leave duration by substituting for a portion of the change in effort with a function of working hours before and after maternity leave, and employ instrumental variables to address the remaining heterogeneity. Finally, I evaluate the change in human capital for each worker and net it out from the disparity in wage growth driven by motherhood to deduce the proportion of the wage growth that is due to effort reallocation.

A new empirical evidence on the origins of wage losses associated with motherhood follows from using the alternative decomposition strategy. The results suggest that, on average, child care is more time consuming than energy consuming. On average, workers do not change their hourly work effort upon return to the labor force from maternity leave. The estimated wage losses are mainly driven by foregone human capital accumulation while on maternity leave, implying that the assertion that women with children exert less work effort is not well supported in the data.

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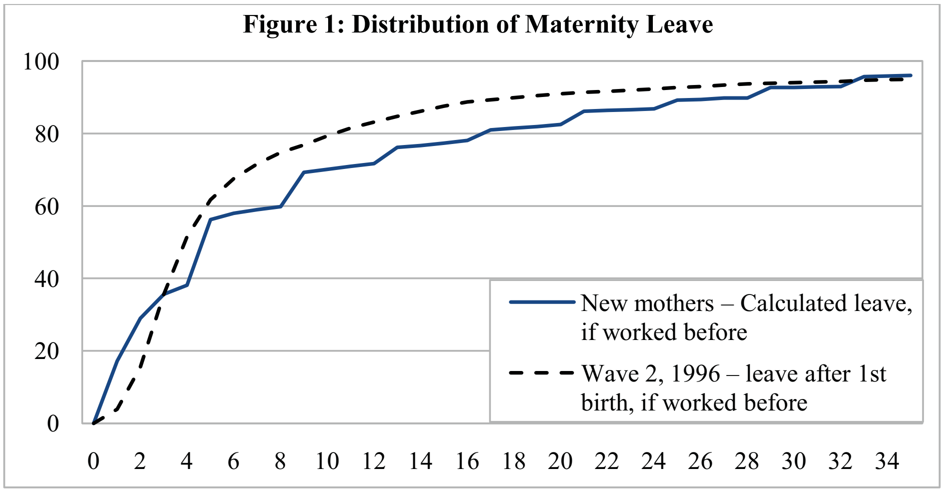

Table 1: Summary Statistics, SIPP sample

	New Mothers, N=1252[1]		Non-Mothers, N=4610[1]	
	Mean	SD	Mean	SD
Hourly wage before	15.07	8.99	14.83	9.21
Hourly wage after	14.58	9.81	14.92	9.34
Hours before	37.91	9.63	37.96	9.43
Hours after	35.00	10.92	37.93	9.15
Leave	5.38	7.03	5.55	6.80
Education	14.33	2.50	13.98	2.26
Age	31.16	5.18	36.67	5.68
Black	0.07	0.25	0.09	0.29
Metro status	0.80	0.40	0.77	0.42
# of children before	0.94	1.06	1.45	1.13
Spousal education	13.97	2.62	13.75	2.44
Spousal wage before	3156	1731	3291	2012
Spousal wage after	3199	1913	3405	2110
Spousal hours before	43.95	9.48	43.39	8.71
Spousal hours after	43.87	9.01	43.37	8.71
Changed industry	0.26	0.44	0.09	0.28
Changed occupation	0.28	0.45	0.11	0.32

Note: To measure hours before I use observations 12 months or more before childbirth. Therefore, statistics for hours before are calculated using 993 and 4610 observations respectively.

Table 2: Summary Statistics, ATUS-CPS and ATUS samples

	ATUS-CPS, one child, weekdays N=150		ATUS-CPS, one child, weekdays + weekends N=277		ATUS, children below 2 years old N=395		ATUS, children below 5 years old N=499	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Child care - physical	1.38	1.45	1.31	1.32	1.34	1.53	1.24	1.40
Child care – total	2.74	2.24	2.64	2.13	2.62	2.21	2.47	2.08
Education	14.47	2.21	14.45	2.32	14.61	2.03	14.55	2.06
Spousal education	14.01	2.03	13.94	2.18	14.18	2.18	14.16	2.16
Spousal income	3596	2243	4324	2074				
TDI	0.15	0.36	0.13	0.34				
Metro status	0.82	0.39	0.83	0.38				
Age	32.61	4.82	32.56	4.69	33.40	7.88	33.52	7.54
Black	0.04	0.20	0.03	0.18	0.05	0.21	0.05	0.21
Spousal hours after	37.35	7.50	36.33	7.10	36.20	7.33	36.48	7.34

Table 3: Estimating the Family Gap, Effects of Childbirth on Wage Rates and Hours Worked

	Δln (w)	ln w_{after}	Δln $(w)_{before}$	ln w_{before}	Δln (h)	ln h_{after}	ln h_{before}
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Birth: [0, 1]	-0.0486	-0.0423	0.0130	0.0064	-0.0948	-0.1291	0.0107
	(0.0121)	(0.0163)	(0.0160)	(0.0160)	(0.0139)	(0.0160)	(0.0140)
Birth*Leave			0.0001				
			(0.0035)				
Leave			0.0025				
			(0.0006)				
Education	0.0007	0.1059	0.0029	0.1052	-0.0008	0.0032	0.0060
	(0.0019)	(0.0029)	(0.0018)	(0.0030)	(0.0016)	(0.0021)	(0.0021)
Age	-0.0164	0.0971	-0.0297	0.1135	0.0072	0.0211	0.0240
	(0.0084)	(0.0112)	(0.0076)	(0.0120)	(0.0081)	(0.0099)	(0.0094)
Age^2	0.0002	-0.0012	0.0004	-0.0014	-0.0001	-0.0003	-0.0003
	(0.0001)	(0.0002)	(0.0001)	(0.0002)	(0.0001)	(0.0001)	(0.0001)
Black	0.0078	-0.0346	0.0128	-0.0424	0.0217	0.0868	0.0846
	(0.0161)	(0.0214)	(0.0145)	(0.0206)	(0.0113)	(0.0125)	(0.0120)
Metro	-0.0066	0.1847	0.0026	0.1913	-0.0042	0.0005	0.0036
	(0.0100)	(0.0153)	(0.0093)	(0.0155)	(0.0091)	(0.0121)	(0.0119)
# of children	0.0092	-0.0092	0.0047	-0.0184	-0.0033	-0.0455	-0.0584
	(0.0042)	(0.0062)	(0.0037)	(0.0064)	(0.0035)	(0.0048)	(0.0045)
const	0.3815	-0.9201	0.5528	-1.3016	-0.1429	3.2372	3.1468
	(0.1424)	(0.1839)	(0.1324)	(0.1971)	(0.1417)	(0.1705)	(0.1607)
N	5862	5862	5420	5862	5603	5603	5603
R2	0.0054	0.2837	0.0090	0.2857	0.0233	0.0467	0.0398

Note: Robust standard errors in parentheses.

Table 4: First Stage Estimations: "log(Hours Ratio)" and Maternity Leave on Education Variables, Spousal Income and TDI[1]

	ATUS-CPS				SIPP	
	Hours Ratio:		Proxy for Hours Ratio:			Maternity Leave, M
	only workdays	including weekends	only workdays	including weekends		
	(1)	(2)	(3)	(4)	(5)	(6)
Mother's educ	-0.0026	-0.0010	-0.0032	-0.0024	-0.0012	-0.5862
	(0.0034)	(0.0028)	(0.0018)	(0.0015)	(0.0004)	(0.0595)
Father's educ	0.0046	0.0053	-0.0020	0.0004	0.0013	0.0749
	(0.0049)	(0.0038)	(0.0025)	(0.0019)	(0.0005)	(0.0604)
Ln(Sp. Inc.)	-0.0366	-0.0280	-0.0223	-0.0121	-0.0218	-2.2260
	(0.0148)	(0.0119)	(0.0100)	(0.0080)	(0.0055)	(1.4662)
Ln(Sp. Inc.)^2	0.0033	0.0025	0.0020	0.0011	0.0021	0.2676
	(0.0013)	(0.0010)	(0.0009)	(0.0007)	(0.0005)	(0.1209)
TDI	-0.0006	0.0032	0.0040	0.0063	-0.0033	0.4346
	(0.0195)	(0.0172)	(0.0120)	(0.0103)	(0.0016)	(0.4668)
Metro status	0.0415	0.0334	0.0146	0.0105	0.0028	-0.7033
	(0.0158)	(0.0118)	(0.0098)	(0.0076)	(0.0014)	(0.6089)
Age	0.1720	0.1339	-0.0332	-0.0349	0.0199	-6.8051
	(0.0944)	(0.0776)	(0.0596)	(0.0460)	(0.0049)	(1.6344)
Ln(Sp. hours)	0.0064	0.0089	0.0249	0.0167	-0.0235	-7.8484
	(0.0322)	(0.0287)	(0.0164)	(0.0156)	(0.0186)	(4.3168)
# of children					-0.0038	0.4080
					(0.0006)	(0.3342)
const	-1.5675	-1.2338	0.3798	0.3620	-0.1204	104.4120
	(0.9106)	(0.7436)	(0.5798)	(0.4450)	(0.0717)	(25.0998)
N	150	277	150	277	1252	1252
R2	0.2625	0.1915	0.1095	0.0510	0.0658	0.0691

[1] TDI – Temporal Disability Insurance, state indicator.

Note: Robust standard errors in parentheses. Estimates include age^2, age^3, black [0,1], $\ln(\text{spousal hours})^2$.

Table 5: Validity of Instruments: Is Mothers' Time Spent on Child Care Correlated with Education Variables and Spousal Income?

	Children below 2 years old, N=393					
	Physical Child Care			Non-Physical Child Care		
	(1)	(2)	(3)	(4)	(5)	(6)
Mother's educ	-0.0007		-0.0010	0.0023		0.0023
	(0.0033)		(0.0033)	(0.0022)		(0.0024)
Father's educ	-0.0014		-0.0017	-0.0325		-0.0024
	(0.0029)		(0.0028)	(0.0114)		(0.0019)
Ln(Spousal Inc.)		0.0003	-0.0026		0.0096	0.0094
		(0.0131)	(0.0123)		(0.0065)	(0.0070)
Ln(Spousal Inc.)^2		0.0000	0.0003		-0.0007	-0.0007
		(0.0011)	(0.0011)		(0.0005)	(0.0006)
Age	-0.0368	-0.0429	-0.0370	0.0008	-0.0326	-0.0321
	(0.0166)	(0.0148)	(0.0171)	(0.0003)	(0.0107)	(0.0117)
Ln(spouse hours)	0.0360	0.0382	0.0356	-0.0019	-0.0038	-0.0057
	(0.0312)	(0.0304)	(0.0304)	(0.0048)	(0.0194)	(0.0196)
Ln(spouse hours)^2	-0.0093	-0.0099	-0.0094	-0.0023	-0.0005	-0.0001
	(0.0079)	(0.0079)	(0.0078)	(0.0021)	(0.0049)	(0.0050)
const	5.1927	5.2418	5.2021	5.1537	5.1454	5.1420
	(0.1833)	(0.1866)	(0.1992)	(0.1281)	(0.1274)	(0.1315)
r2	0.0485	0.0471	0.0496	0.0257908	0.0294	0.0330

	Children below 5 years old, N=499					
	Physical Child Care			Non-Physical Child Care		
	(1)	(2)	(3)	(4)	(5)	(6)
Mother's educ	-0.0006		-0.0007	0.0019		0.0020
	(0.0027)		(0.0027)	(0.0018)		(0.0020)
Father's educ	-0.0019		-0.0020	-0.0025		-0.0024
	(0.0025)		(0.0024)	(0.0017)		(0.0017)
Ln(Spousal Inc.)		0.0040	0.0005		0.0086	0.0077
		(0.0106)	(0.0100)		(0.0055)	(0.0061)
Ln(Spousal Inc.)^2		-0.0003	0.0000		-0.0007	-0.0006
		(0.0009)	(0.0009)		(0.0005)	(0.0005)
Age	-0.0256	-0.0315	-0.0261	-0.0194	-0.0207	-0.0201
	(0.0136)	(0.0126)	(0.0137)	(0.0106)	(0.0106)	(0.0111)
Ln(spouse hours)	0.0304	0.0303	0.0291	0.0058	0.0016	0.0003
	(0.0247)	(0.0238)	(0.0236)	(0.0155)	(0.0155)	(0.0157)
Ln(spouse hours)^2	-0.0081	-0.0082	-0.0079	-0.0023	-0.0015	-0.0013
	(0.0063)	(0.0062)	(0.0062)	(0.0039)	(0.0040)	(0.0040)
const	5.0729	5.1117	5.0781	5.0005	5.0005	4.9990
	(0.1539)	(0.1586)	(0.1635)	(0.1247)	(0.1281)	(0.1294)
R2	0.0379	0.0351	0.0386	0.0168609	0.0185	0.0219

Note: Robust standard errors in parentheses. Estimates include age^2, age^3, black [0,1].

Table 6: Validity of Instruments: The Relationship between Hardship of Child Care,[1] Education Variables and Spousal Income (Mothers) , N=531

	(1)	(2)	(3)
Mother's educ	-0.0058		-0.0038
	(0.0142)		(0.0144)
Father's educ	-0.0035		-0.0024
	(0.0130)		(0.0132)
Ln(Spousal Income)		-0.0013	-0.0084
		(0.0519)	(0.0540)
Ln(Spousal Income)^2		-0.0018	-0.0008
		(0.0058)	(0.0062)
Age	-0.0575	-0.0685	-0.0571
	(0.1915)	(0.1901)	(0.1918)
Ln(spousal hours)	0.0869	0.0969	0.0902
	(0.3015)	(0.3025)	(0.3034)
Ln(spousal hours)2	-0.0248	-0.0216	-0.0212
	(0.0508)	(0.0515)	(0.0516)
const	2.1502	2.1864	2.1410
	(2.0507)	(2.0573)	(2.0634)
R2	0.0166	0.0182	0.0187

[1] Using self reported answer to the question: "My children are much harder to care for than most children. How often do you feel this way? 1. Never; 2. Sometimes; 3. Often; 4. Very often.

Note: Robust standard errors in parentheses. Estimates include age^2, age^3, metro status [0,1], black [0,1].

Table 7: Evaluating Human Capital Depreciation Rate (δ): OLS & IV Estimates of the Log Hourly Wage Change Equation, "New Mothers"

	OLS		TSLS			
					alternative instruments	
					net-worth & spousal income	state indicators
1st stage:			ATUS	SIPP	SIPP	SIPP
	(1)	(2)	(3)	(4)	(5)	(6)
Maternity Leave (δ)	-0.0061	-0.0068	-0.0107	-0.0119	-0.0117	-0.0119
	(0.0017)	(0.0017)	(0.0054)	(0.0061)	(0.0088)	(0.0070)
Ln(Hours Ratio)[1]		1.1240	2.0996	2.8901	2.0142	-0.2313
		(0.4715)	(1.3829)	(1.4336)	(2.5637)	(0.6605)
Metro status	-0.0262	-0.0314	-0.1074	-0.0255	-0.0190	-0.0179
	(0.0279)	(0.0273)	(0.0573)	(0.0127)	(0.0131)	(0.0133)
Age	-0.1784	-0.2005	-0.5965	-0.3542	-0.3426	-0.2584
	(0.1116)	(0.1138)	(0.1794)	(0.0858)	(0.1846)	(0.1285)
Black	-0.0246	-0.0132	0.1036	0.0211	0.0053	-0.0221
	(0.0419)	(0.0414)	(0.1013)	(0.0711)	(0.0376)	(0.0534)
Ln(Spousal hours)	0.6051	0.6837	-0.7406	-0.5264	-0.5002	-0.5091
	(0.3910)	(0.3961)	(0.4439)	(0.4569)	(0.4425)	(0.4596)
Ln(Spousal hours)^2	-0.0943	-0.1061	0.1089	0.0641	0.0585	0.0674
	(0.0588)	(0.0593)	(0.0670)	(0.0621)	(0.0593)	(0.0637)
# of children	0.0110	0.0162	0.0234	0.0313	0.0216	0.0166
	(0.0122)	(0.0121)	(0.0139)	(0.0167)	(0.0154)	(0.0113)
const	1.2083	1.2564	7.6083	5.1748	4.8887	4.0216
	(1.3470)	(1.3812)	(2.4029)	(1.0380)	(1.4728)	(1.5178)
N	1252	1252	1252	1252	1220	1252

Note: Robust standard errors in parentheses. Estimates include age^2, age^3.

Table 8: Evaluating Human Capital Depreciation Rate (δ): OLS & IV Estimates of the Log Hourly Wage Change Equation, "New Mothers", Job Stayers

	OLS	OLS	TSLS
	(1)	(2)	(3)
Maternity Leave (δ)	-0.0061	-0.0072	-0.0135
	(0.0035)	(0.0033)	(0.0091)
Ln(Hours Ratio)		2.1843	5.3475
		(0.6352)	(3.2428)
metro	-0.0239	-0.0256	-0.0356
	(0.0291)	(0.0286)	(0.0213)
Age	-0.1393	-0.1868	-0.2995
	(0.1313)	(0.1306)	(0.0588)
Black	-0.0743	-0.0577	-0.0104
	(0.0574)	(0.0553)	(0.0291)
Ln(Sp. hours)	-0.8275	-0.7894	0.3987
	(0.4600)	(0.4971)	(0.4866)
Ln(Sp. hours)2	0.1247	0.1191	-0.0533
	(0.0671)	(0.0718)	(0.0703)
# of children	-0.0032	0.0035	0.0167
	(0.0134)	(0.0131)	(0.0138)
const	3.0152	3.3390	2.3127
	(1.6210)	(1.6685)	(1.2190)
N	888	888	888
R2	0.0185	0.0413	

Note: Robust standard errors in parentheses. Estimates include age^2, age^3.

Table 9: Evaluating Human Capital Depreciation Rate (δ): OLS Estimates of the Log Hourly Wage Change Equation, Selectivity Adjusted Results

	OLS	Selectivity adjusted	
	(1)	(2)	(3)
Maternity Leave (δ)	-0.0068	-0.0071	-0.0070
	(0.0017)	(0.0018)	(0.0017)
Ln(Hours Ratio)[1]	1.1240	1.0459	1.0305
	(0.4715)	(0.4666)	(0.4684)
Metro status	-0.0314	-0.0305	-0.0265
	(0.0273)	(0.0272)	(0.0275)
Age	-0.2005	-0.2056	-0.2268
	(0.1138)	(0.1129)	(0.1114)
Black	-0.0132	-0.0144	-0.0102
	(0.0414)	(0.0414)	(0.0424)
Ln(Sp. hours)	0.6837	0.6948	0.5131
	(0.3961)	(0.3910)	(0.4172)
Ln(Sp. hours)2	-0.1061	-0.1079	-0.0839
	(0.0593)	(0.0586)	(0.0619)
# of children	0.0162	0.0157	0.0147
	(0.0121)	(0.0121)	(0.0121)
const	1.2564	1.3074	1.8742
	(1.3812)	(1.3655)	(1.3860)
N	1252	1332	1332

Note: Estimates include age^2, age^3. Estimates in column (2) are obtained using the month of child's birth as instrumental variable in the first-stage estimations. Estimates in column (3) use mother's education, father's education, spousal income and spousal income squared as instruments in the first-stage estimations.

Table 10: Estimations of Net Accumulation Rate of Human Capital, Change in Log Wage as Dependent Variable, Non-Mothers Sample[1]

	(1)	(2)	(3)	(4)
Leave1	0.0022	0.0023	0.0022	0.0022
	(0.0007)	(0.0007)	(0.0007)	(0.0007)
Education	0.0029	0.0034	0.0026	0.0031
	(0.0022)	(0.0024)	(0.0026)	(0.0027)
Age	-0.0326	-0.0326	-0.0336	-0.0341
	(0.0109)	(0.0108)	(0.0107)	(0.0107)
Age2	0.0004	0.0004	0.0005	0.0005
	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Black	0.0165	0.0177	0.0156	0.0160
	(0.0171)	(0.0170)	(0.0172)	(0.0171)
Metro status	0.0129	0.0110	0.0138	0.0125
	(0.0111)	(0.0111)	(0.0111)	(0.0111)
# of children before	0.0039	0.0040	0.0031	0.0033
	(0.0043)	(0.0043)	(0.0043)	(0.0043)
const	0.5929	0.6341	0.6638	0.6637
	(0.1903)	(0.1965)	(0.1961)	(0.1953)
Inds		+		+
Occs			+	+
N	4610	4610	4610	4610
R2	0.0064	0.0090	0.0129	0.0144

[1] First-differences wage equation for non-mothers is constructed around an arbitrary period. Arbitrary spell is randomly assigned using the percentage distribution of maternity leave of new mothers.

Note: Robust standard errors in parentheses.

Table 11: Estimating Motherhood Wage Loss with Adjusted Log Wage Change (α=0.2% and δ is as specified)

	Δln(w)	Δln(w) - |estimated change in human capital|	
		δ=1%	δ=0.6%
	(1)	(2)	(3)
Birth	-0.0486	0.0117	-0.0141
	(0.0121)	(0.0121)	(0.0119)
Education	0.0007	-0.0005	-0.0002
	(0.0019)	(0.0019)	(0.0019)
Age	-0.0164	-0.0216	-0.0200
	(0.0084)	(0.0084)	(0.0084)
Age2	0.0002	0.0003	0.0003
	(0.0001)	(0.0001)	(0.0001)
Black	0.0078	0.0102	0.0097
	(0.0161)	(0.0161)	(0.0161)
Metro	-0.0066	-0.0067	-0.0052
	(0.0100)	(0.0100)	(0.0099)
Children	0.0092	0.0097	0.0095
	(0.0042)	(0.0042)	(0.0042)
const	0.3815	0.4867	0.4530
	(0.1424)	(0.1425)	(0.1412)
N	5862	5862	5862
r2	0.0054	0.0041	0.0032

Note: Robust standard errors in parentheses.