After Motherhood: Effects of Maternity Leave and Effort Reallocation on Earnings

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Abstract

It is well documented that women with children earn less than women without children. To study this wage gap I construct a dynamic model of human capital accumulation in a setting where labor force participation is endogenous and labor supply is measured by hours and effort. The model establishes relationships between optimal maternity leave duration and time and effort allocations before and after the leave. I employ the model to address the key explanations found in the family gap literature: the effects of career interruptions, time and energy demands of child care and selection into motherhood. Using theoretical predictions, I develop an empirical decomposition strategy to evaluate each explanation. The results suggest that the main reason for lower wages of mothers is the loss of human capital. On average, mothers do not reduce their work effort. Also, I find no evidence that the motherhood wage gap is driven by selection.

Keywords: *motherhood wage gap; human capital; time allocation; effort allocation.*
JEL classification: *C52, J22, J24, J31.*

1 Introduction

The negative impact of motherhood on individual wages is a well-established empirical fact (see for example Hill, 1979 and Waldfogel, 1998). This family wage gap has remained significant over decades, and has been widening (for review, see Waldfogel, 1998), simultaneously with the narrowing gender gap. Most women will eventually have children and there persists strong social and economic pressure for mothers, not fathers, to spend more time caring for children.[1] Researchers have cited the motherhood wage penalty to be as large as a 5 to 10 percent per child in a cross-sectional

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[1] Women who had at least one child by the age of 40 constitute 90% of all women, according to the 1996 and 2001 Survey of Income and Program Participation data. Likewise, 70% of all mothers participate in the labor force.

analysis; while male workers' wage rates were found to be positively associated with children (see for example Lundberg and Rose, 2000). While these facts seem well established, it is less clear how the motherhood wage penalty is generated.

Two questions in the existing literature are about the extent to which the relationship between children and wages is causal, and about the mechanism by which motherhood affects wages. One question is whether the negative relationship between number of children and wage reflects child-related reduction in productivity, or whether it simply reflects the selection of lower-productivity women into childbearing. Two possible sources for such selection are heterogeneity in unobserved characteristics, such as career-orientedness, and endogenous fertility. Both suggest that women with low current or expected market productivity are more likely to become mothers. Some studies address selection issues by employing fixed effects techniques. (See for example, Korenman and Neumark, 1994; Waldfogel, 1998 and England and Budig,1999.) Most of these studies report that controlling for unobserved individual characteristics reduces the family gap, but a significant portion of it remains unexplained.

Several theories try to explain the remaining difference in earnings. The dominant hypothesis addresses the effects of work interruptions on wage rates. Time spent on maternity leave may reduce market productivity through a of loss of human capital during the period out of the labor force. Many researchers who employ this reasoning control for actual work experience while estimating the family gap, (for instance, Waldfogel, 1998 and Anderson, Binder and Krause's, 2002); this procedure usually reduces the unexplained portion of wage difference, but in most cases cannot explain it entirely.

Some studies also posit that caring for children is effort consuming, which implies that women with primary responsibility for child care have less energy available for the market activities relatively to childless women. Less energy at work translates into lower productivity, which in turn leads to lower wages. The pioneer study to model this relationship belongs to Becker (1985), where he introduces time and energy constraints and analyzes female and male household and work activities and labor market outcomes. In this work Becker shows how persons devoting much time to effort intensive households activities, like child care, would economize on their use of energy at work. Due to data limitations (effort is not observable in most datasets), a direct test of Becker's hypothesis is not feasible.[2] However, many researchers relate the unexplained portion of the family gap to effort demands of child care.

In the current work I develop a dynamic version of Becker's (1985) framework, combined with learning-by-doing human capital accumulation, to account for both the effects of work interruptions on human capital depreciation and the energy constraints. I use this model to analyze the movements in wages of women around the time of birth, and to decompose the decline in wage growth associated with children. Wage growth (or loss) is constructed using pre- and post-motherhood wage rates,[3] a formulation that nets out selection issues.[4] I attribute the remaining difference in earnings to two

[2] Some studies address unobservable energy demands of children by introducing occupational indicators (see for exampe Budig and England (2001)) and child's age group indicators (Anderson et. al. (2002)). Using those controls cannot eliminate the wage gap entirely. Further discussion of those approaches is provided in the following section.

[3] To construct wage growth equation for the control group, women who did not have children during the relevant period, I use wage rate observations around an arbitrary period.

[4] Selection issues are assessed separately. Selection into fertility timing is addressed by comparing pre-pregnancy wages of future mothers and women who will not have children during the survey course. I find no evidence that future

factors: effects of work interruptions on human capital and effort reallocation. The first channel relates to the human capital hypothesis. While on maternity leave new mothers' human capital depreciates, while that of women who were continuously employed accumulates. Additionally, new mothers must reallocate their effort across activities to meet tightening time and energy constraints, this channel is in line with the work-effort hypothesis. I employ the theory to derive a set of empirically testable implications and assess the two key explanations.

Childbirth induces a tightening of time and energy constraints, which in turn requires reallocation of time and effort spent on all activities. It is not definite which way effort will adjust. Generally, if child care is a more time demanding rather than effort demanding activity, working hours may decline, but hourly effort exertion at work may increase. This result will be reversed if child care is more energy than time consuming activity. Without further information about the modifications in time and energy constraints it is impossible to assess how much time and effort are adjusted, especially when child care demands are heterogeneous across individuals. Additionally, when labor market participation is endogenous the maternity leave decision is likely to be correlated with time and effort allocations. These correlations can arise due to observable factors, like education, assets and spousal income, and due to unobservable factors - time and effort demands of children. Abstracting from these correlations (due to the fact that work effort is unobservable) can lead to a biased estimate of human capital depreciation and to incorrect decomposition of children-related wage losses.

I decompose the wage growth difference in two steps. First, I estimate the effects of change in human capital on wage growth. These estimations yield measures of depreciation and accumulation rates of human capital. Where obtaining a consistent measure of human capital depreciation rate is the most demanding step of the estimation process. Then 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.

I specify wage rate growth (or loss) as a function of maternity leave and unobservable effort reallocation and evaluate the depreciation rate of human capital using a subsample of new mothers whose human capital had potentially depreciated during maternity leave. The set of variables which are correlated with maternity leave but orthogonal to effort reallocation is limited, since similar forces drive both choices. This implies that instrumental variables methods cannot be implemented. To that end, I employ model predictions about the negative trade-off between time and effort allocations: spending fewer hours on energy intensive activity allows a mother to increase effort exertion on all activities, and I use a measure of hours worked before and after the maternity leave to proxy for the change in unobservable effort.

However, this substitution may not entirely resolve the endogeneity issues. A portion of the change in effort which is driven by unobservable time and effort demands of children is likely to remain. To address this remaining heterogeneity I employ the instrumental variables technique. Using working hours instead of work effort in the wage growth specification expands the instruments set to all variables correlated with maternity leave, but orthogonal to time and effort demands of children. The choice of instruments is directed by the decision making process about time and

childbearing affects current wage rates. Additionally, since the data shows that 90 percent of women have a child by the age of 40, this result implies that mothers are not a selected group.

effort allocations and the choice of maternity leave duration. Observable individual fixed effects (education variables, spousal income and state policy indicator about maternity leave payments), that determine one's marginal utility of wealth are utilized as instrumental variables. The appeal of these variables is that they are uncorrelated by construction with the individual error component in the first differences wage equation, as well as with the time and effort demands of children, as follows from various validity tests. Thus, this two-stage estimation procedure allows me to obtain a consistent estimate of the human capital depreciation parameter. The other parameter of the human capital accumulation process, the net accumulation rate, is derived using wage observations of women who were continuously employed and did not have children during the survey course.

With estimates of human capital accumulation process parameters in hand, I can disentangle the sources of wage growth disparity associated with maternity. To achieve this goal I complete one more step. I evaluate the change in human capital for each worker and net it out from the disparity in wage growth driven by motherhood. Then, I perform difference-in-differences analysis using the entire sample of female workers to deduce the proportion of the wage growth that is due to effort reallocation.

To perform empirical analysis I draw from multiple datasets: 1996 and 2001 Survey of Income and Program Participation (SIPP), 2003 - 2007 American Time Use Survey (ATUS) and Current Population Survey (CPS). Using SIPP the mean birth related wage rate loss is estimated to be around 6.5 percent. I first estimate what portion of this gap is due to foregone human capital. I show that women who stay longer out of the labor force on maternity leave tend to earn lower hourly wages when they return to the market. Using the instrumental variables approach, the monthly depreciation rate of human capital is estimated to be around 1 percent. I show that 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 evaluated at 0.2 percent. Mean duration of maternity leave is 5.5 months, which implies that the failure to accumulate human capital while on leave explains more than 95% of the wage loss experienced by mothers, leaving little room for effort reallocation to explain the gap.

The remainder of the paper is organized as follows: Section 2 summarizes the existing literature. Section 3 builds the theorethical framework, which establishes the relationship between market time and effort, as well as the origins for correlations between maternity leave and time and effort allocation. Section 4 discusses the data and methods of selecting the key variables. In Section 5 I outline the empirical strategy, discuss the validity of the instruments used in the first stage of the estimations and provide the results. Here I also investigate the plausibility and magnitude of the estimates. Section 6 concludes the paper.

2 Literature Review

This paper contributes to the ongoing discussion on the causes of the family gap. A number of hypotheses have been put forward in the literature studying the family gap.

Human capital accumulation and depreciation during work interruptions have received a large amount of attention in the family gap literature, and in the labor economics literature in general. Studies by Altug and Miller (1998) and Cossa, Heckman, and Lochner (2000) find a significant effect of past work experience on current wage earnings. It is also well documented that displaced workers suffer important wage losses (for example see Jacobson, LaLonde, and Sullivan, 1993) and that wage profiles are affected by job tenure (Topel, 1991). These findings suggest that experiencing an interruption in labor force participation should have an important effect on labor market outcomes. In the family gap literature, in an early study conducted by Hill (1979), the addition of labor force attachment variables, such as experience and tenure, to regression models eliminates mothers' penalty. However, other research that has controlled for human capital levels has still found motherhood to have a persistent negative effect. In a study by Waldfogel (1998), even after controlling for education and experience, mothers faced a 4 percent wage penalty for one child and a 9 percent penalty for two or more children. Mincer and Polasheck (1974), Light and Ureta (1995) also find that human capital depreciation during the interruption plays an important role in explaining the gap but cannot explain it entirely.

Some authors have argued that selection is the main explanation for the family gap. Korenman and Neumark(1992) examine how unobserved heterogeneity, endogeneity of experience, tenure, marriage and motherhood can explain the family gap. They find an insignificant coefficient for the one-child penalty when they control for actual experience and job tenure. The penalty for more children is preserved but reduced by more than half.[5] Korenman and Neumark(1994) and England and Budig (1999) find a negative selection as well. However, they conclude that unobserved heterogeneity cannot fully explain the penalty associated with motherhood. In a more recent paper, Lundberg and Rose (2001) find that mothers who experiences an interruption in employment 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 heterogeneity cannot explain the entire wage loss associated with children.

Implications of Becker's work-effort explanation were examined in a few studies. Anderson, Binder and Krause (2002) use a fixed effects framework to perform econometric analysis to examine whether reduced work effort can provide an explanation for the family gap. They control for unobserved heterogeneity and actual experience. To proxy for energy demands at home, Anderson et al. use the age of the child upon return to the labor market. Occupation dummies are used to proxy for exerted effort at work. These reduce the gap, but do not explain it entirely. The authors find no evidence that child's age upon return to work plays a significant role. They conclude that hours allocation and flexibility in time spent at work are the main reasons for the family gap. The work-effort hypothesis is also investigated by Phipps, Burton and Lethbrigde (2001) in a cross-sectional model, who argue that the more time women spend on housework and child care, the less energy they have for their labour market careers. By including numbers of hours spent on unpaid work in the estimation they find that the child penalty declines, but remains significant. Budig and England (2001) attempt to control for mothers' effort levels by adding occupation variables to their human capital model. Neither the addition of these variables, nor any other job characteristic variables, changed the child penalty. But it is not clear that occupation dummies can capture much of the heterogeneity in household demands. Waldfogel (1995) provides another indirect test of the effort hypothesis by arguing that, if the hypothesis is true, single mothers with presumably greater child

[5] Waldfogel (1997) argues that short differences understate the penalty, because the majority of women were still on maternity leave. She estimates fixed effects models using short and longer differences and finds that the motherhood penalty increases with the child age.

care responsibilities should have greater effort related wage penalties. She finds that this is not the case if one conditions on education and work experience and concludes that time spent at work and hours flexibility are more important in explaining the family gap than effort exertion.

This short summary of the existing literature suggests that the discipline is uncertain about what determines the family gap. There exist papers that address the human capital explanation together with selection into motherhood. However, except for Anderson, Binder and Krause's (2002) empirical analysis, I am not aware of a work that employs both energy demands of motherhood and human capital depreciation in a fixed effects framework, to explain the family gap. The largest body of research has been directed towards examining the importance of mothers' time out of the labor force and lower working hours as an explanation for their lower wages – the "human capital" hypothesis. But an implicit assumption in the studies cited above is that the duration of maternity leave, that affects human capital and, therefore, wages, is independent of market effort allocation.[6] However, if the choice maternity leave is interrelated with the effort reallocation decision, the standard identification method may lead to biased results. In the current work, using a dynamic framework, where working time, effort and maternity leave are determined simultaneously, I explicitly allow for correlations between the length of maternity leave and time and effort allocations. I propose an alternative decomposition method which accounts for this endogeneity.

3 The model

3.1 The Environment

This section suggests a dynamic model of female labor supply where both time and effort can respond. The analysis focuses on the sequential choice process of female workers, who adjust their labor supply to accommodate time and energy demands of child care. There are several main building blocks of the model. I apply the static framework of time and effort allocation from Becker (1985), with time and energy constraints, in a dynamic setup to which I add a learning-by-doing human capital accumulation process and fixed costs of work. Addition of human capital to the basic model is due to its importance in the wage generation process, as has been suggested by numerous studies. The role of fixed costs of work was found to be considerable in determining labor supply behavior of married women by, for example, Cogan (1981). The proposed additions to Becker's (1985) specifications allow for a more complete formulation of the maternity leave choice and of the post-birth allocations of time and energy.

To specify a mechanism that generates a motherhood wage gap I consider women before and after a childbirth. Three variables define wages at each phase 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. Thus, a worker's decision of how long to spend on maternity leave affects her wages upon return to the labor force. All decisions are made when taking as given the birth decision.[7] Also, for simplicity, I abstract from

[6] There are studies that consider endogeneity of labor market experience or work interruptions (for example see Ejrnæs and Kunze (2004)). However, in these studies the choice of instruments is driven by different assumptions about the source of endogeneity.

[7] Exogenous fertility timing assumption is supported by the findings in the SIPP data - there is no systematic difference in pre-prgnancy wages, labor supply or other observable characteristics between future mothers and women

uncertainty about time and effort demands of yet-to-be-born children.

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 market consumption, $c(t)$, and effective leisure, $\widetilde{l}(t)$, where t denotes the agent's current age and $t \in [0, T]$. 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 in a similar manner, $l(t) = n(t)f(t)^{\sigma}$. Where $n(t)$ and $f(t)$ are time and effort per hour spent on market activities; ρ and σ are the elasticities of effective home and market time with respect to effort exertion, where $0 < \rho,\ \sigma < 1$. I assume that market work is more energy intensive than housework and leisure activities,[8] which implies $\rho < \sigma$. Each worker is endowed with fixed stocks of time and energy that must be allocated across activities during 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,

$$\begin{cases} \widetilde{n_i}(t) + n_i(t) = 1 & \forall t <= B \\ n_i(t) + \widetilde{n_i}(t) + \eta_i(t) = 1 & \forall t > B \end{cases}. \tag{1}$$

Workers with children have fewer hours to allocate to leisure and market activities if child care time, η_i, is positive. Those time requirements of child care are given and known to worker at time 0, and are not a choice variable. I assume that η_i is log-normally distributed.[9] Heterogenous η implies that individuals may face different time constraints after a childbirth. Individual's time constraints will affect her choice of maternity leave duration and subsequent time and effort reallocations.

It is a consensus that child care is a time and effort intensive activity, as discussed, for example, by Becker (1965) and Becker (1985); and that the presence of children will tighten time and effort constraints. A good example of child care demands in this context is basic physical care of children - activities that the parents must perform and cannot avoid, and therefore can be treated as exogenously given. Heterogeneity in time demands of children might be driven, among others, by child's health and personality, parents' experience with children or parents' philosophy of childcare.

I define $f(t)$ and $\widetilde{f_i}\ (t)$ to represent effort levels per hour the worker exerts at work and at home. There is an upper limit for the total energy the worker can exert on both activities. The energy constraint takes the following form

$$\begin{cases} n_i(t)f_i(t) + [1 - n_i(t)]\,\widetilde{f_i}(t) = 1 & \forall t <= B \\ n_i(t)f_i(t) + [1 - n_i(t) - \eta_i(t)]\,\widetilde{f_i}(t) + \eta_i(t)\phi_i(t) = 1 & \forall t > B \end{cases} \tag{2}$$

This constraint presents workers with an additional trade-off: working more intensely in the market results in less energy for non-market activities. Energy demands of children are given by ϕ. For simplicity I assume that ϕ is constant across new mothers.

who will not have children in the near future (Table 1, columns 3 and 7).

[8] This assumption is discussed extensively by Becker (1985) and used by other authors as well, including Bils and Chang (1998).

[9] The choice of the distribution of η is directed by American Time Use Data, 2003 - 2007, where time spent on child care is recorded.

When children are born the worker has to reallocate her time and effort spent on all activities to satisfy the new energy and time constraints. As will be discussed in the following subsection, workers with more significant time demands of children may lower their hours and increase their effort at work;[10] this is possible since more energy is conserved while spending time out of the labor force, this preserved energy can be redistributed over all activities.

Employing the energy constraint, the formulation of effective work at home can be rewritten as follows:

$$\widetilde{l}_i(t) = \begin{cases} (1-n_i(t))\left(\frac{1-n_i(t)f_i(t)}{1-n_i(t)}\right)^{\rho} & t \leq B_i \\ (1-\eta_i)\left(\frac{1-\eta_i\phi}{1-\eta_i}\right)^{\rho} & B_i < t \leq B+M_i \\ (1-n_i(t)-\eta_i)\left(\frac{1-n_i(t)f_i(t)-\eta_i\phi}{1-n_i(t)-\eta_i}\right)^{\rho} & t > B+M_i \end{cases} \tag{3}$$

The agent chooses her consumption stream, $c_i(t)$, hours 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

$$U[c_i(t), \widetilde{l}_i(t), M_i] = \int_0^T e^{-\theta t} u\left[c_i(t)\right] dt + \int_0^{B_i} e^{-\theta t} v\left[\widetilde{l}_i(t)\right] dt + \int_{B_i}^{B_i+M_i} e^{-\theta t} v\left[\widetilde{l}_i(t)\right] dt + \int_{B+M}^{T} e^{-\theta t} v\left[\widetilde{l}_i(t)\right] dt. \tag{4}$$

Where θ is the rate of time preference and it is assumed that $\theta > 0$. 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 periods, before having a child, during maternity leave, and after the return to the labor force, are distinguished by discrete jumps in utility the agent receives from effective leisure, $v\left[\widetilde{l}_i(t)\right]$, as given in (3). The present value of lifetime utility is written as the sum of values obtained during each stage of the life-cycle.

Non-labor income is given by income from 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 $W(t)$, fixed costs of work, $z_i(t)$, (i.e. commuting, child care) and a constant interest rate $r > 0$, budget constraint for an individual i in period t is given by:

$$a_i(t) + c_i(t) \leq a_i(t-1)(1+r) + b_i(t) + W_i(t) - z_i(t) \tag{5}$$

Worker's wage is a function of working hours, effort level and human capital, formulated as:[11] $W_i(t) = H_i(t)n_i(t)f_i^{\sigma}(t)$.

Total worker productivity, $n_i(t)f_i^{\sigma}(t)$, depends on both inputs - time and effort - given the elasticity of effective market time with respect to effort exertion, σ. $\sigma < 1$ implies that increases

[10] In Becker (1985) it is assumed that the intensity of housework/ leisure is higher when children are present. Here I distinguish between child care and other housework/ leisure by altering time and energy constraints. This enables workers to adjust both factors of effective labor supply, time and effort.

[11] Involuntary unemployment is not considered, that is, any individual can find a job at the relevant wage.

in effort per hour have diminishing effects on earnings, while equal effort input is used with each hour. Firms compensate workers for the total amount of effective labor they provide. By entering $f_i(t)$ explicitly it is assumed that firms can monitor effort. For simplicity, I abstract from firms' decisions. A general equilibrium framework that introduces effective labor can be found in Becker (1977) which provides a full analysis of these decisions.

Human capital accumulates over time according to past labor market participation. Human capital stock in period t equals to human capital in preceding period $H_i(t-1)$ plus new human capital produced. This dependence is summarized by the following representation:

$$\begin{aligned} \dot{H}_i(t) &= \alpha p_i(t) H_i(t) - \delta H_i(t). \\ H_i(0) &= H_{i,0}. \end{aligned}$$

Here the learning-by-doing parameters, δ and α, correspond to depreciation and accumulation rates. I define $p_i(t)$ to be the indicator of labor market participation, $p_i(t) = 1$ if $n_i(t) > 0$ and $p_i(t) = 0$ otherwise.

The wealth constraint is given by the following equation,[12]

$$\begin{aligned} \int_0^T e^{-rt} c_i(t) dt &= a_{i,0} + \int_0^B \left[H_{i,0} e^{(\delta-d-r)t} n_i(t) f_i^{\sigma}(t) - e^{-rt} z_i(t) \right] dt + \\ & \int_{B+M}^T \left[H_{i,0} e^{-\delta M} e^{(\delta-d-r)t} n_i(t) f_i^{\sigma}(t) - e^{-rt} z_i(t) \right] dt + \int_0^T e^{-rt} b_i(t) dt, \end{aligned} \tag{6}$$

where agent's consumption and effective leisure streams and the duration of maternity leave must satisfy: $c_i(t), \widetilde{l}_i(t) \geq 0, \forall t$, and $0 \leq M_i \leq T_i - B_i$.

The logarithm of observed hourly wages of agent i evolves according to the following specification:

$$\ln w_{it} = \sigma \ln f_{it} + \ln H_{it} + \upsilon_{it}.$$

where $w_{it} = \frac{W_{it}}{n_{it}}$ and υ_{it} summarizes measurement error in the data. Human capital evolves according to the learning by doing model, where H_0 can be interpreted as an individual specific effect (e.g. ability).

Lagging human capital for D periods (where $D \geqslant 1$) yields the following expressions:

$$\begin{cases} \ln w_{it} = \sigma \ln f_{it} + \ln H_{i,t-D} + (\alpha - \delta) D + \upsilon_{it}, & if \;\; P_{i,D} = 1 \\ \ln w_{it} = \sigma \ln f_{it} + \ln H_{i,t-D} - \delta D + \upsilon_{it}, & if \;\; P_{i,D} = 0 \end{cases} \tag{7}$$

where $P_{i,D}$ indicates whether worker i was employed ($P_{i,D} = 0$ if i spent D periods out of the labor

[12] Three accounting identities are used to specify the wealth constraint:
$H_{i,B_i} = H_i(B_i) = H_{i,0} e^{(\delta-d)B_i}$,
$H_{i,B+M} = H_i(B_i + M_i) = H_{i,B} e^{-dM_i}$,
$H_i(t) = H_{i,B_i+M_i} e^{(\delta-d)[t-(B_i+M_i)]}, \quad \forall t > B_i + M_i$.

force) during the D periods.

Using the specification in (7), I construct empirically testable difference-in-differences equation to evaluate wage rate losses associated with motherhood:

$$\ln w_{it} - \ln w_{i,t-M_i} = \sigma(\ln f_{it} - \ln f_{i,t-M_i}) + (\alpha - \delta)M - \alpha(1 - P_{i,M})M + (\ln \upsilon_{it} - \ln \upsilon_{i,t-M_i}) \,, \quad (8)$$

where M is the maternity leave measure for new mothers, or an arbitrary spell for non-mothers. $P_{i,M} = 0$ indicates that the worker was on maternity leave during those M periods. In econometrical terms, $(1 - P_{i,M})$ should be replaced by a binary indicator for a childbirth.

Equation (8) formulates the mechanism that generates wage change before and after maternity leave. The first term summarizes the effect of effort reallocation of new mothers (given that non-mothers this term is practically zero). The interaction between maternity leave and birth dummy variable (the third term in the equation) sums wage losses associated with forgone human capital accumulation while out of the labor force. Unfortunately, channels that generate this wage differential cannot be identified using available datasets. Effort is not observable and estimation results of equation (8) will be biased if the change in effort is correlated with duration of maternity leave. This relationship is established in the following subsections.

3.2 Model Analysis

3.2.1 First Order Conditions

Hereafter the i-subscript is dropped for ease of notation.

Worker chooses over consumption, market time, market effort and duration of maternity leave to maximize her utility. Optimization yields four first order conditions.

The first order condition for consumption, $c(t)$, is

$$u'\left[c(t)\right] = \lambda \frac{e^{-rt}}{e^{-\theta t}}, \quad \forall t, \quad (9)$$

where λ is the multiplier on the budget constraint in the Lagrangian (i.e. λ is the marginal utility of wealth in period 0). The consumption is chosen such that the marginal utility of consumption equals the marginal utility of wealth after adjusting for discount factor which depends on the rate of time preference and the rate of interest.

For periods with positive hours worked I obtain the following conditions. The first order condition for hours of work, $n(t)$, is

$$v'\left[\widetilde{l}(t)\right] = \lambda \frac{e^{-rt}}{e^{-\theta t}} \frac{\widetilde{n}(t)}{n(t)} \frac{w(t)}{\widetilde{l}(t)} \frac{1}{\left(1 - \rho + \rho \frac{f(t)}{\widetilde{f}(t)}\right)}. \quad (10)$$

And the first order condition for the hourly effort input at work, $f(t)$, is

$$v'\left[\widetilde{l}(t)\right] = \lambda \frac{e^{-rt}}{e^{-\theta t}} \frac{\sigma}{\rho} \frac{\widetilde{f}(t)}{f(t)} \frac{\widetilde{n}(t)}{n(t)} \frac{w(t)}{\widetilde{l}(t)}. \tag{11}$$

Equalities in equations (10) and (11) means that positive amounts of time and effort are supplied to the market.

The first order condition for the duration of maternity leave, M, is

$$e^{-\theta M}\left[v\left[(1-\eta)\left(\frac{1-\eta\phi}{1-\eta}\right)^{\rho}\right] - v\left[(1-n(B+M)-\eta)\left(\frac{1-n(B+M)f(B+M)-\eta\phi}{1-n(B+M)-\eta}\right)^{\rho}\right]\right] \geq$$
$$\lambda H_0 e^{-\delta M}\left\{e^{(\delta-d-r)(B+M)} n(B+M) f^{\sigma}(B+M) + \int_{B+M}^{T} e^{(\delta-d-r)t} n(t) f^{\sigma}(t) dt - e^{-r(B+M)} z\right\}, \tag{12}$$

with equality for $M > 0$. The left-hand-side of the equation is the marginal cost of returning to work one period earlier since it is the sum of the instantaneous gain in utility the agent receives from one period on leave and the fixed costs of work. The right-hand-side is the marginal benefit since it represents the gain in earnings the agent gets by working in moment M. The gain in earnings from shorter leave comes from two sources. First, the additional earnings the agent gets from working in moment M increase her utility value. Second, all earnings through time T are affected, since there is no human capital accumulation while on leave.

3.2.2 Characterization of the Optimal Conditions with Empirical Implications

This section looks at the relationship between the key parameters of the model, effective labor supply and worker's optimal maternity leave.

As was specified earlier, equation (8) describes the mechanism that generates wage losses associated with motherhood:

$$\ln w_t - \ln w_{t-M} = \sigma(\ln f_t - \ln f_{t-M}) + (\alpha - \delta)M - \alpha(1 - P_M)M + (\ln \upsilon_t - \ln \upsilon_{t-M}).$$

This equation cannot be correctly decomposed if the change in effort is not observed but is correlated with the maternity leave. Equation (12) shows that the duration of maternity leave can be presented as an implicit function of λ, η, H_0 and B. Additionally, hourly market effort and, in the general case, the change in market effort, $\Delta \ln f_t$, are implicit functions of λ, η, H_0 and B as well. Therefore, there are three potential sources for this correlation: marginal utility of wealth, time demands of children and level of human capital at time of birth. In the general case, the optimal duration of maternity leave, M^*, and the change in exerted effort at work, $\frac{f_M}{f_0}$, are correlated. (Proof is provided in Appendix).

A few examples demonstrate how these correlations affect the accuracy of estimation of equation (8). Higher assets, raising lifetime wealth, should prolong maternity leave and may lower post-birth hourly work effort. Unobservable time and effort demands of children are also likely to affect both choices. For example, if time demands of motherhood were relatively more important than energy demands, workers with children would conserve on time away from home by decreasing their hours worked at the market and increasing their effort inputs. In general, maternity wage loss will not be accurately decomposed if there is a correlation between the effort and the length of maternity leave. The example demonstrates a case where the depreciation rate of human capital is overstated and a smaller portion of the maternity wage loss remains unexplained. However, it is also possible that both time and effort inputs are reduced upon the return to the labor force, this is the likely case when energy demands of children are relatively high. Since the unexplained remainder of the wage loss is interpreted as the average change in effort, it is important to have an idea about the size and the direction of the correlation between the change in effort and maternity leave to identify the true effects of each factor.

The relationship between the two decisions signifies the inference problem of the estimation process: both variables are driven by the same forces, which implies that the set of valid instruments for maternity leave is limited. To address this issue I employ the trade-off between effort and (observable) hours of work to substitute for change in effort. However, as shown below, this substitution is not sufficient to obtain consistent estimates since it captures only a portion of the change in effort. Endogeneity which is driven by unobservable time and effort demands of children remains. The main gain from this substitution is that it relaxes the validity requirements of instruments. Instead of searching for variables uncorrelated with the change in effort, it allows me to employ instruments which are orthogonal to the exogenous time and effort demands of children. Therefore, by utilizing the trade-off between time and effort I expand the set of available instruments, and can specify a transparent estimation strategy.

To supply effective labor to the market, workers make two decisions: they choose hours and effort to exert per hour. These two decisions are interrelated and connected through the energy constraint - the more hours the worker wishes to supply to the high energy intensive activity - market work, the fewer hours she will be able to supply to that activity. This relationship between effort exerted at work and hours supplied is immediately derived from the hours and effort first order conditions and the energy constraint:

$$f(t) = \frac{\Gamma(1 - x(t)\eta\phi)}{n(t)\,(\Gamma - 1) + (1 - x(t)\eta)}, \tag{13}$$

where $\Gamma = \frac{\sigma}{\rho}\frac{1-\rho}{1-\sigma}$.

The presence of children requires adjustments in labor supply. Controlling for hours, the main change in the allocation of time and effort is implied directly by time and energy demands of child care. Employing equation (13) lets me derive change in market effort before and after work interruption as a function of hours supply before and after a childbirth (or, before and after any arbitrary M periods):

$$\frac{f_M}{f_0} = (1 - x_M\eta\phi)\frac{n_0\,(\Gamma - 1) + 1}{n_M\,(\Gamma - 1) + (1 - x_M\eta)} \tag{14}$$

where f_0 is the the hourly effort prior to work interruption (or, a childbirth) and f_M represents exerted effort upon return to the labor force (M periods later), $x_M \in [0, 1]$ and indicates presence of children in period M. The size of the change in effort cannot be specified without further assumptions about parameters and state variables at the time of birth. $\frac{f_M}{f_0}$ depends on the values of time and effort demands of children, η and ϕ, and on the change in hours, n_0 vs. n_M, where $n(t) = n\left[\lambda, \eta, H_0, B, x(t); \sigma, \rho, \phi\right]$. For instance, effort per hour at work may increase if time demands of children are more important than energy demands. In this case, spending time on child care does not require much effort, which allows one to distribute the conserved energy on all other activities. Alternatively, energy spent per hour of market activity can also decrease if child care is more effort intensive than time consuming.[13] Generally, post-birth hourly work effort can increase or decrease. (Proof is provided in Appendix).

Substituting change in effort from equation (14) into equation (8), and using wage observations before and after maternity leave (i.e. $P_M = 0$ and $x_M = 1$) delivers

$$\triangle \ln w = \sigma \ln \left[\frac{n_0 \left(\Gamma - 1\right) + 1}{n_M \left(\Gamma - 1\right) + (1 - \eta)} \right] - \delta M + \sigma \ln(1 - \eta\phi) + \triangle v. \tag{15}$$

Parameter Γ was calibrated by Bils and Chang (1999). Γ equals the ratio between energy inputs at work and at home.[14] Bils and Chang evaluate this parameter by using information from Passmore, et. al. (1974), in the World Health Organization publication *Handbook on Human Nutritional Requirements*, who present energy expenditures (in calories) for work in various occupations as well as for a range of leisure activities. Based on these calorie use data, they set the ratio Γ at $\frac{3}{2}$. I use this value to construct the first term of equation (15); I also explore the robustness of the results to this choice of Γ.

Maternity wage loss mechanism is described in equation (8). The mechanism specifies that the wage disparity between mothers and non-mothers is driven by two channels, effort reallocation by new mothers and their forgone human capital while on maternity leave. However, the equation cannot be estimated directly since effort is not observable. To evaluate what generates the wage loss I perform a two step decomposition strategy, while in each step I assess a different source of this disparity. First, I obtain consistent measures of the human capital accumulation process. The depreciation rate is estimated using equation (15). The net accumulation rate is assessed using a similar specification but for women who were continuously employed, (i.e. estimating equation (8) for workers with $P_M = 1$ and $x_M = 0$). With estimates of parameters of human capital accumulation process in hand I proceed and evaluate how new mothers' effort reallocation affects their wage loss.

The most demanding step of the estimation procedure is obtaining a consistent estimate for human capital depreciation using equation (15).

Equation (15) can be consistently estimated using the OLS method if time and effort demands of children, η and ϕ, are observed or constant across mothers. If η and ϕ are heterogeneous but observed, then the estimation procedure is straightforward. In this case, reallocation of effort is measured using equation (14) and both parameters of equation (15) can be unbiasedly estimated. If time and effort demands of children are unobserved but do not vary across mothers, then OLS

[13] In this setting, for simplicity purposes, I abstract from the possibility that child care costs positively depend on the working hours. In this case, there is an additional incentive to reduce the working time and to increase the hourly work effort.

[14] $\Gamma = \frac{\sigma}{\rho}\frac{1-\rho}{1-\sigma} = \frac{f}{\tilde{f}}$, as follows from equations (2), (8) and (9).

analysis will provide a consistent estimate of the depreciation rate, δ.[15]

When time demands of children are unobserved and vary across new mothers, controlling for hours will not be enough to identify the true parameters of the equation. Unobservable time demands of children enter equation (15) twice, and create multiple inference problems. First, η enters the equation non-linearly via the hours ratio. Approximating the denominator of the hours ratio with $\ln\left[n_M(\Gamma-1)+(1-\bar{\eta})\right]$, where $\bar{\eta}$ is a mean time requirement of child care, will result in a non-linear nonclassical measurement error. Presence of such measurement error implies that standard linear instrumental variable approach might provide inconsistent results. In addition, η appears in the error term, $\ln(1-\eta\phi)$. Therefore, given that η is correlated with the duration of maternity leave and time reallocation decisions,[16] the presence of unobservable and heterogeneous time demands of children imposes two potential channels through which OLS estimations will be biased. Moreover, non-linearity of the error term requires using methods different from the standard IV estimation.

The IV method was developed for models that are linear in the mismeasured variables. IV estimators might be biased in nonlinear models. Therefore, I use a different approach to address the inference problems. Availability of data and problem specification allow application of a Two Sample TSLS estimation introduced by Angrist and Krueger (1992, 1995). Two Sample TSLS (TSTSLS) statistical procedure is particularly useful whenever two data sets share a common set of instruments, but the endogenous regressors and the dependent variable are not jointly included in both data sets. In the current context, the first-stage regression of $\ln\left[\frac{n_0(\Gamma-1)+1}{n_M(\Gamma-1)+(1-\eta)}\right]$ is estimated using data from the combined sample of American Time Use Survey and Current Population Survey (hereafter, ATUS-CPS; 2003 - 2007). This data set includes measures of hours, time spent on child care and the set of instruments, but it is limited in the number of observations and 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) - activities that depend on a child's characteristics and are not choice variables. Detailed description of the data set is provided in the following section.

I estimate the first stage of maternity leave deciosion and the second stage equations using the main dataset, Survey of Income and Program Participation (hereafter, SIPP; 1996, 2001), where all variables of equation (15) but η and ϕ are available. (The data set is described momentarily in the following section). Additionally, I use SIPP to explore the robustness of the first stage results obtained using the ATUS-CPS sample; in these estimations I use the mean value of time spent on physical child care from ATUS-SPS, $\ln\left[\frac{n_0(\Gamma-1)+1}{n_M(\Gamma-1)+(1-\bar{\eta})}\right]$. Note that the vector of instruments, Z, contains precisely the same set of variables in all first stage specifications. Conditional on relevant and valid instruments for the hours ratio and for the maternity leave, the described procedure should eliminate biases due to the presence of unobservable error term, $\ln(1-\eta\phi)$, in the regression, as well as any biases due to classical measurement error in the measure of maternity leave. The estimated coefficients form the regressors, $\ln\left[\frac{\widehat{n_0(\Gamma-1)}+1}{n_M(\Gamma-1)+(1-\eta)}\right]$ and $\widehat{M}$, which are used in the second-stage estimations.[17]

All first stage estimations use similar instrumental variables. The choice strategy of the instruments is driven by theoretical predictions about time allocation and maternity leave decision making

[15] This conclusion is driven from a simulations analysis. Plugging different values of η into the first term of equation (15) reveals that parameter $\widehat{\delta}$ is unaffected. While $\widehat{\sigma}$ depends on the value of η.

[16] See Appendix for additional notes.

[17] A detailed technical discussion of the estimation procedure is provided in the empirical section.

process. The lifetime budget constraint, equation (6), implicitly determines the optimal value of the marginal utility of wealth, λ. Thus, λ 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 birth and time and energy demands of children. As discussed above, marginal utility of wealth affects both maternity leave and time allocation decisions.[18] Therefore, the observable elements of λ which are uncorrelated with time demands of children, can be used to instrument for maternity leave and hours worked. I employ education, spousal education, spousal income and state policy indicator - whether paid maternity leave is available, to instrument for hours ratio and maternity leave.

Instrumental variables should satisfy validity conditions, which require that the instruments are correlated with $\ln\left[\frac{n_0(\Gamma-1)+1}{n_M(\Gamma-1)+(1-\eta)}\right]$, but are uncorrelated with $\ln(1-\eta\phi)$. I address this validity condition in the empirical section.

Using the above described estimation strategy to evaluate the parameters of equation (15) provides a consistent measure of the depreciation rate, δ. Estimating equation (8) for women who did not have children and who were continuously employed through the observed period (i.e. $P_M = 1$ and $x_M = 0$) lets me evaluate the net accumulation rate of human capital, $(\alpha-\delta)$. To construct wage growth for this subsample of workers I randomly assign the percentage distribution of maternity leave to women who did not have a child during the relevant period and calculate the difference between pre- and post-"leave" wage rates. To obtain the net accumulation rate I examine the relationship between the assigned "leave" and the change in logarithm of wage rate. With both parameters in hand I can neutralize the effects of change in human capital on wage growth and evaluate the remaining source of the difference between new mothers and non-mothers - effort reallocation upon child birth, by comparing their adjusted wage rate differences.

The final step of the decomposition procedure is to estimate

$$\ln w_t \widehat{- \ln} w_{t-M} = \sigma(\ln f_t - \ln f_{t-M}) + (\ln \upsilon_t - \ln \upsilon_{t-M}),$$

where $\ln w_t \widehat{- \ln} w_{t-M} = \ln w_t - \ln w_{t-M} - M\left(P_M\widehat{\alpha} - \widehat{\delta}\right)$. The final step evaluates the mean effect of effort reallocation by new mothers on the disparity in wage growth (given that continuously employed mothers did not change their effort allocations).

4 Data

4.1 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 is well suited for this analysis. It 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 therefore has observations across 36 months. In some instances, answers were

[18]See Appendix for additional notes on the relationships between time allocation and maternity leave decisions and the observable elements of marginal utility of wealth.

obtained for each month in the four month reference period, in other cases questions were directed to obtain information for the entire 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. The advantages of using the SIPP include its longtitudal structure, monthly frequency and the variety of variables available for all family members. The SIPP is unique in being a large, nationally representative data set that tracks the employment variables (hours and earnings) of both mothers and fathers in the period immediately before and after a birth. Other datasets track this information at the time of the survey only (Current Population Survey) and for mothers only (National Longitudinal Surveys).

To study the effects of childbirth on female labor market outcomes I restrict the sample to married couples only, with wives between the ages of 18 and 45. Individuals must not be in the armed forces, not disabled and not attending school full time. Also, I do not use observations for individuals who are missing any key variables (i.e. hours, earnings, age, educations, etc.). The raw sample used in this study contains information on 20,707 women (and their husbands), of whom 3,736 had a child during the course of the panel.[19] New mothers with at least one wage observation before and after birth count 1252 cases.[20] "Non-mothers" with continuous wage observations constitute 4667 observations.[21] Some specifications consider only observations of workers who participated in the labor market 12 months before the birth, in those regressions the number of observations is smaller.

The dependent variable in most of the analysis is the change in log of the real hourly wage rate on the main job (in 2000 US dollars). To construct the change I use averages of wage before and wage after the maternity leave. I use wages reported from 12 to 3 months prior to birth to construct the "before" measure.[22] Wages observed 1 to 12 months after the return from maternity leave are used to obtain the wage "after".[23] 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).

Descriptive statistics of the variables used in this paper are presented in **Appendix Table 1**. The summaries are shown separately for the two groups of women, those who had a child during the survey course, and those who did not. Women who had delivered a child are fairly similar to women in the control group in education, race, and labor force outcomes before the childbirth. Their hours worked and wage rate after return to the labor force are significantly lower than those of women who were continuously participating and did not have children. Women who did not have a child during the survey course are older (by 5 years on average) and have more children (0.5 more, on average); older age is also the reason their spouses have higher income.

The maternity leave variable is based on the spell duration of new mothers out of the labor force immediately following a birth, unless the leave started prior to birth. The SIPP records employment

[19] If parents had more than one child during the panel (as about 10% the sample did), I included only the last child.

[20] I use the term "new mothers" to classify women who gave birth during the survey period. The last child is the relevant one for analysis purposes. "New mothers" can have previous children.

[21] The control group is constructed from women who did not have a child during the survey. Like "new mothers", "non-mothers" may have previous children.

[22] I do not include the last two months in the measure of hours before since some women change their work schedule significantly in the final months of pregnancy (for medical or other reasons).

[23] Since data collection is done on a four months basis, I obtain the most updated measure of the wage "after" by using observations collected during the wave that started after return to the labor fource. This procedure was intended to reduce the measurement error in the data.

activity in several ways. Respondents report their labor market status as of each week during the survey month and summarized information about their monthly labor force status is available as well. A leave that started before and up to 3 months after the birth date is considered as valid. Once the worker is observed participating in the labor force the maternity leave is concluded. The maternity leave measure is limited since SIPP tracks only unpaid leaves. Then, if paid leave was not followed by some period of unpaid leave - leave duration will be recorded as zero months. If using only the weekly employment status, many new mothers, around 25%, (some of which seem to be due to a pure measurement error, and some due to paid leave). Those 25% should be compared to 4% of zero leaves reported in the Wave 2, 1996; which records the actual length of maternity leave taken after giving birth to first child. For women who do not report any leave I take a few more steps. First, I update the maternity leave measure by using other available labor status variables: monthly employment status, hours worked, monthly earnings. Second, during the second wave of the 1996 survey, female respondents are asked about their fertility history and they also report the length of maternity leave taken after their first birth. For women with zero months of leave, who remained with the same employer since their first child, I correct the duration of leave to the one reported in the second wave. The 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, Rhode Island and railroad industry employees are entitled to at least 6 weeks of paid leave, provided by Temporary Disability Insurance (TDI).[24] For these women I correct the maternity leave period from zero months to the shortest period offered by the law in their state, 1.5 months.[25] This reduces the fraction of zero leaves to 15%. The construction of this measure for maternity leave might introduce measurement error, which will be considered in the empirical section. Moreover, as a robustness check, empirical estimations are performed using all and only non-zero maternity leave durations. The coefficients in both regression specifications are very similar, as shown later in the paper.

For comparisons between new mothers and women who did not have children during the survey course I construct "leave" periods for the latter group as well. For non-mothers it is a random variable, drown from the percentage distribution of maternity leave provided in the second wave of SIPP 1996.

The distribution of the duration of maternity leave of women who worked prior to having a child is shown on **Appendix Figure 1**. The descriptive statistics of maternity leave are provided in **Appendix Table 1**. Mean maternity leave spell is measured to be 5.4 months.

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

SIPP data does not provide any information about time spent caring for children. Therefore, first stage estimations and validity tests of the instrumental variables that require information about

[24] The temporary disability insurance laws of the five states cover most commercial and industrial wage and salary workers in private employment if the employer has at least one worker. A claimant must have a specified amount of past employment or earnings to qualify for benefits. However, in most jurisdictions with private plans, the plans either insure workers immediately upon their employment or, in some cases, require a short probationary period of employment, usually from 1 to 3 months. (Annual Statistical Supplement, 2006, U.S. Social Security Administration)

[25] Generally, employers that provide TDI, along with its other benefits must cover pregnancy and childbirth as well. Since the federal Pregnancy Discrimination Act of 1961, all disability insurance policies must cover "pregnancy-related" disability. Thus, these five states make TDI benefits available to women who have corroboration from a physician that they are 'disabled' for a period of time before/after the birth of a child.

time demands of children cannot be performed using the SIPP. Thus, to evaluate the validity of the utilized instruments in both first stage estimations of equation (15) I use data from the 2003-2007 waves of the American Time Use Survey (ATUS) conducted by the U.S. Bureau of Labor Statistics. In first stage estimations of equation (15), I utilize merged data of both 2003-2007 ATUS and Current Population Survey (CPS). ATUS data contains measures of time spent with children. Merging ATUS with CPS allows me to observe both the change in working hours around birth and time spent carrying 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 I use only information collected on weekdays and non-holidays only. I accommodate the sample such that it is compatible with the SIPP sample used in main estimations. 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. Since it is impossible to specify which child in the household received particular child care, I specify a subsample where I include only respondents with one child under two years old (the relevant age group for SIPP estimations). This subsample counts 393 observations of mothers. (Married women with one child below 5 years old count 499 observations)

For the analysis I employ two definitions of child care. "Physical child care" is any time spent on the basic needs of children, including breast-feeding, rocking a child to sleep, general feeding, changing diapers, providing medical care (either directly or indirectly), grooming, etc. This type of child care that accounts primarily for physical care activities is the most suitable to represent time demands of children (time spent on those activities is expected to be not a choice variable). “Non-physical child care" is the sum of any time spent on education (reading to children, teaching children, attending meetings at a day care center, etc.), and on recreational child care (playing games with children, playing outdoors with children, going to the zoo with children, and taking walks with children). **Appendix Table 2** displays 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 that contains only female respondents with small children. Since questions about usual weekly hours/earning are asked only at households in their 4th and 8th interview, I merge ATUS subsample with observations collected during outgoing rotations of CPS.[26] 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 I use weekend data

[26] This is possible because starting in 2002, some households that were in the final survey month of their CPS interview were selected to participate in the ATUS. Households are interviewed once a month for four months, are out of the CPS rotation for 8 months, and then are surveyed again for another 4 months. The "final" month is the last month of the second set of four months. Households were randomly selected from the CPS to participate in the ATUS, with the exception of an over-sampling of households with children and Hispanics. Moreover, the ATUS does not match the CPS' oversampling of less populous states.

as well, which increases the merged ATUS-CPS sample to 277 observations. Descriptive statistics for these data are given by **Appendix Table 2.**

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

5 Empirical Analysis

Having established a framework where allocations of market time and effort and the duration of maternity leave are endogenous, I now investigate empirically the origins of childbirth-related wage loss. First, I discuss the limitations of the standard family gap estimations. I argue that the correlation between maternity leave duration and effort reallocation decisions may lead to biased decomposition of the motherhood wage penalty. Then I use the alternative decomposition strategy to evaluate each channel. I first net out selection issues by constructing wage growth using pre- and post-motherhood wage rates.[27] Then, using this specification, I estimate the effect of human capital changes during the work interruption spell on wage growth. Finally, this information is used to deduce the proportion of the wage growth that is due to effort reallocation.

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.

5.1 The Limitations of Basic Family Gap Estimations

Hourly wage rates are specified by the following equations:

$$\ln w_{it-M} = \sigma \ln f_{it-M} + \ln H_{it-M} + \upsilon_{it-M}, \tag{16}$$

$$\ln w_{it} = \sigma \ln f_{it} + \ln H_{i0} + (\alpha - \delta)t - \alpha(1 - P_M)M + \upsilon_{it}, \tag{17}$$

where $\ln H_{i0} + (\alpha - \delta)(t - M) = \ln H_{it-M}$, $\ln H_{i0} + (\alpha - \delta)t - \alpha(1 - P_M)M = \ln H_{it}$ and P_M indicates whether the worker was employed during the M periods, and practically, $(1 - P_M)$ is an indicator for having a child. M specifies maternity leave taken by new mothers, or an arbitrary time spell for women who did not have children during the survey course. H_0 is a function of worker's ability and background, unobservable to the econometrician. For practical purposes, the total family gap can be estimated by using a form of equation (17):

$$\ln w_{it} = \beta Birth + \ln H_{i0} + \upsilon_{it}, \tag{18}$$

where β summarizes the average of $((\alpha - \delta)M - \alpha Birth M + \sigma \Delta \ln f_{it})$ and the differences in unobservable characteristics if mothers were a selected group. $Birth$ is a binary variable that equals 1 if the worker spent time out of the labor force on maternity leave, and zero otherwise. The control group in this specification, $Birth = 0$, includes only continuously employed non-mothers. Estimating

[27] The wage growth equation for the control group is constructed around an arbitrary period.

equation (18) represents the most common approach to assess motherhood effects on wage, where *Birth* is usually replaced by a vector of dummy variables that summarize the number of children in the household.

Taking first differences, by substructing equation (16) from equation (17), lets me to net out selection. Wage change of new mothers can be measured by taking wage observations before and after maternity leave. For women who did not have a child during the survey period, I construct wage growth around a random spell assigned according to new mothers' leave distribution. The first differences equation of the hourly pay rate between periods t and $t - M_i$ is given by equation (8) and takes the form:

$$\Delta \ln w_{it} = \sigma \Delta \ln f_{it} + (\alpha - \delta)M - \alpha BirthM + \Delta v_{it}, \tag{19}$$

Disparity in wage growth between mothers and non-mothers can arise from two sources: change in exerted effort and loss of human capital accumulation while on maternity leave. An attempt to summarize all unobservables by introducing a dummy variable for having a child reduces to the following equation:

$$\Delta \ln w_{it} = \beta Birth + \Delta \psi_{it_i}, \tag{20}$$

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 multiple studies that evaluate family gap (here I use a recent birth indicator instead of the more common estimation with a vector of indicators for number of children). Since equations (18) and (19) are often used in the literature to measure the family gap, for comparison purposes I present their estimation outcomes here. However, those specifications do not allow to quantify the family gap into loss of human capital and adjustment in effort inputs, the ultimate goal of this work.

Estimating Family Gap: Selection, Human Capital or Change in Work Effort? **Table 1** displays the results from estimations of (16), (18) and (19) and (20). The first column of **Table 1** provides estimates of equation (19), changes in the logarithm of real hourly wages. The coefficient of the *Birth* dummy variable in this regression (-6.5%) summarizes the mean total motherhood wage loss, which, by assumption, is driven by the foregone human capital while on leave and by the childbirth related effort reallocation. The second column displays the results obtained by estimating equation (18), logarithm of real hourly wages after the return to the labor force. In addition, to the productivity related wage loss the coefficient of the *Birth* indicator in this regression also reflects any wage losses (or gains) which are driven by selection into motherhood. The *Birth* coefficient in the second column (-5%) is lower than in the first column, implying that there is no negative selection into motherhood. Results displayed in the third column reinforce this conclusion. The estimated coefficient of the future birth indicator suggests that there is no negative selection into birth timing or motherhood. Women who will have children during the sample course do not appear to earn lower wages than those of women who will not. The fact that over 90 percent of the women in the SIPP had children by the age of 40, providing an additional support for the conclusion that mothers are not a selected group.

The estimated family gap, 6.5 percent in the first difference specification, is comparable to estimates found in the existing literature. For example, using fixed effects models Anderson, Binder and Krause (2002) find this gap to be around 3%, while Waldfogel (1997) estimates it to be around 6%. In a cross-sectional analysis Anderson et. al. and Waldfogel (1997) found the wage penalty for one child to be 4% - 7%, also comparable to the 5% found here.

Most of the control variables do not affect this gap, except for the indicators of industries and occupations, the addition of which reduces the gap to 5% (not shown). Since industry and occupation variables are endogenous it is not clear whether placing them in this kind of regression is correct. Additional discussion about the occupational choice is provided later in the paper.

How is this gap decomposed into change in effort, forgone human capital accumulation and selection? Estimation results of the wage rate equations presented in **Table 1** suggest that selection is not important in generation of the family gap. Similar specifications for hours worked[28] lead to the same conclusion. Childbirth has a strong negative effect (-12%) on hours worked after the return to the labor force, however the data does not show any significant negative effect of future birth on hours worked before the pregnancy.

Then, the next step is to decompose this gap into changes in market effort and human capital. Effort is not observable, and equation (19) cannot be directly estimated. However, I can proxy for the change in effort by using an indicator for recent childbirth, assuming that only new mothers reallocated their energy inputs between activities. These results are displayed in column (4) of **Table 1**. The birth indicator coefficient reduces to -2%, which implies that the role of human capital in wage growth disparity mechanism is important. On the other hand, meaningful statements about the sources of the gap cannot be made if the maternity leave duration is likely to be correlated with the heterogeneous effort reallocation decision. For instance, in the case of positive correlation, the coefficient of the interaction between birth indicator and maternity leave will be biased downward (in absolute value), and the negative effect of effort reallocation on wage growth will be overstated.

In the following subsections I propose and implement a procedure that provides an unbiased decomposition of the wage losses associated with motherhood. I find that the basic estimations as in column (4) of **Table 1** provide biased results, while underestimating the contribution of maternity leave to the wage growth disparity and assigning higher weight to the effort reallocation channel.

5.2 Step I: Estimating the Depreciation Rate of Human Capital

I decompose the motherhood wage penalty in two steps. First I obtain the human capital accumulation process parameters to evaluate the effects of work interruptions on wage rates. The estimation of human capital depreciation rate is the most demanding step. Women who recently had children choose the duration of maternity leave, there is no such decision making for non-mothers. Therefore, I estimate the depreciation rate of human capital by using the sample of women who gave birth during the survey course. Net accumulation rate is relatively simple to derive using a subsample of women who were continuously employed and did not have children during the survey course. In the next step I use the information about human capital depreciation and accumulation to deduce the proportion of the wage growth that is due to effort reallocation.

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

My theoretical model specifies a mechanism (equation (15)) to determine wage losses of new mothers who spent M periods out of the labor force. For empirical estimations I modify it slightly to introduce X_{it}, a set of control variables that should reduce the variation in unobservables, i.e. race, age, number of prior children, etc. Then, I estimate the following specification, where I construct the first term by employing the calibration result,[29] $\Gamma = \frac{2}{3}$:

$$\triangle \ln w_{it} = \sigma \ln \left[\frac{n_0 \left(\frac{2}{3} - 1\right) + 1}{n_M \left(\frac{2}{3} - 1\right) + (1 - \eta)} \right] - \delta M + \sigma \ln(1 - \eta\phi) + \beta X_{it} + \triangle \upsilon_i. \tag{21}$$

The key parameter of interest in equation (21) is the monthly depreciation rate, δ. As discussed earlier, OLS procedure will provide a consistent estimate of δ, (but not of σ), only if there is no variation in unobservable time and effort demands of children across the new mothers, (alternatively, OLS will deliver unbiased results for all coefficients if η is observable). However, if mothers are heterogenous in terms of these variables, estimated coefficients might be biased. Implementing Two-Sample TSLS procedure addresses these heterogeneity issues. I choose instrumental variables from the set of individual fixed effects: education, spousal education, spousal income and state policy indicator - whether paid maternity leave is available (TDI).[30] The theoretical reasoning to employ these variables is that they determine the marginal utility of wealth, which affects labor market choices. From the empirical perspective, these variables are fixed at the individual's level and, therefore, should be uncorrelated by construction with the change in individual specific error component, $\triangle \upsilon_i$. To test for orthogonality between these variables and the remaining error term, $\sigma \ln(1 - \eta\phi)$, I conduct a series of experiments where I explore the correlations between this residual and the instruments. Additionally, I use other instruments, total net worth record and state dummy variables, to examine the robustness of the coefficients. Instrumental variables should not only address the endogeneity issues, but also correct any biases due to a classical measurement error in the measure of maternity leave and/ or hours of work.

5.2.1 First Stage Results

To proxy for the time demands of children, η_i, I use the measure of time spent on providing basic care for children. I carefully choose the composition of this proxy to include only activities which are necessary and cannot be avoided, (i.e. breast feeding, rocking a child to sleep, general feeding, changing diapers, providing medical care, grooming, etc.).[31]

As was highlighted in the earlier section, unobservable variables enter the wage growth equation non-linearly, which introduces a non-linear nonclassical measurement error that requires special attention in the estimation process. I address this issue by implementing a Two Sample TSLS method.

First, I estimate the function of change in hours by using the ATUS-CPS merged data where

[29] As noted earlier, to evaluate the parameter Γ, I use calibration result reported in Bils and Chang (1999).

[30] TDI - Temporal Disability Insurance.

[31] I assume that the activities which are included in this measure are either directed by child's needs or by mother's beliefs about child care. Some children require more attention than others and some parents follow the Ferber method while others do not feel that getting a baby to sleep alone is a worthwhile objective, and instead advocate more time-consuming methods, i.e. cuddling the baby to sleep.

time demands of children are observable. The equation is specified as

$$\ln\left[\frac{n_0\,(\Gamma-1)+1}{n_m\,(\Gamma-1)+1-\eta_i}\right]=Z_i\gamma^n+X_{it}\theta^n+\xi^n, \tag{22}$$

where Z_i is the vector of instruments, which includes education, spousal education, spousal income, spousal income squared and state policy indicator about maternity leave payments. X_i are exogenous regressors used in the second stage (race, age, number of children before the current birth,[32] metro status and and spousal working hours), which are expected to control partially for unobservables. By assumption, instruments are not correlated with the time demands of children and with the error term, $Z_i \perp \eta_i$ and $Z_i \perp \triangle v_i$. I test the first part of this assumption in the next subsection.

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

$$M_i=Z_i\gamma^M+X_{it}\theta^M+\xi_i^M. \tag{23}$$

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

The advantage of this two-stage procedure is directed by data availability: $\triangle \ln w_i$, Z_i, X_i, n_0 and n_M are present in both datasets, SIPP and ATUS-CPS, while M appears only in SIPP and η_i is available only in ATUS. Additionally, ATUS-CPS sample is much smaller than the SIPP sample, which imposes more restrictions on using ATUS-CPS data. Both variables are predicted using the SIPP data and are integrated in the second stage estimations. The standard errors of the structural coefficients are corrected for the fact that a predicted variable is used in the second stage.

Table 2 displays the results from ATUS-CPS data and SIPP data, logarithm of ratio of hours before and after birth on education, spousal education, spousal income, state policy indicator about maternity leave payments and other covariates (race, age, metro status and spousal hours). Consider column (1). The estimates show that there is a strong relationship between change in hours worked and spousal income. This relationship is not linear and implies that spousal income is negatively correlated with change in hours for lower income levels, and positively for higher spousal incomes. Column (2) displays similar outcomes for a bigger sample that includes the 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 me 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 time demands of children. The results in columns (3) and (4), using workdays and all weekdays, are different in magnitudes but show similar directions to those obtained by using the information about time spent on child care.

The last two columns of **Table 2** show estimates that were obtained using the SIPP data. Column (5) presents the results from regressing the proxy of hours ratio, $\ln\left[\frac{n_0(\Gamma-1)+1}{n_m(\Gamma-1)+(1-\overline{\eta})}\right]$, using the SIPP data. Comparing results reported in column (3) to those in column (5) demonstrates that the coefficients of the significant estimates are fairly similar, while the estimates obtained by using SIPP data are based on more observations and therefore measured with higher precision. This result implies that using first stage results for the actual hours ratio obtained using the ATUS-CPS data, as in column (1), is reasonable. To show that the second stage results do not differ significantly

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

depending on which first stage estimates are used, I present the second stage estimates under both scenarios.

The last column of **Table 2**, column (6), displays the results of the maternity leave equation, equation (23), using the SIPP data. These results are in line with the theoretical analysis. Higher education leads to a shorter leave, while higher spousal education prolongs the leave. Spousal income is negatively correlated with maternity leave duration for lower income levels, while this correlation is positive for higher spousal incomes.

5.2.2 Validity of the Instruments

In this subsection I test the assumptions about orthogonality between the instrumental variables (education, spousal education, spousal income, spousal income squared and state policy indicator about maternity leave payments) and the remaining error term, $\sigma \ln(1 - \eta\phi)$. To perform the tests in most cases I use American Time Use Data (ATUS) and Current Population Survey (CPS), 2003 - 2007, since SIPP data does not provide any information about time spent caring for children. In addition to the validity tests, I perform estimations using other instrumental variables (total net worth record and state dummy variables), which produce lower-precision but similar estimation results of the monthly depreciation rate and provide a robustness check, I discuss these results in the following subsection.

Education might be correlated with the child care demands if there is a relationship between child care abilities or beliefs how much time and effort to spend on child care and education. Or, alternatively, spousal education might be correlated with his degree of participation in child raising. For example, Guryan, Hurst and Kearney (2008), using ATUS data, find a positive relationship between education and time spent with children under 18 years old. This finding could undermine the validity of education variables as instruments. In the current work the age of children is limited by the return of the mother to the labor force, such that 95% of children in this study are below 2 years old, therefore including only individuals with small children in the ATUS sample is more practical for the purposes of this study. I choose to test whether there is a relationship between mother's time spent on child care and parental education in families with one child under the age of 2. In those estimations I use only those individuals who during a given day spent some time on physical child care. The outcomes of those estimations are presented in **Table 3**, column (1), which summarizes the results of regressions of the error term[33] on instrumental and exogenous variables used in first and second stage estimations. Presented results suggest that the relationship between education and physical child care is not significant. To explore the robustness of this outcome I regress a measure of time spent on non-physical child care during a given day using similar explanatory variables, those results are given in column (4). The results of these estimations are statistically insignificant but point estimates are higher in absolute values. As an additional robustness check, I perform same estimations for parents of one child below 5 years old, the results are displayed on the lower panel of **Table 3**. These estimates suggest similar conclusions, i.e. no significant correlation between education and time demands of children (when specified as physical child care).

The link between spousal income and lifetime wealth is evident. However, one might suggest that spousal income and time spent on physical child care are correlated. For instance, higher

[33] Error term is given by $(1 - \eta\phi)$ where $\phi = 1$. The estimates are robust for other values of ϕ, with $\phi \in [1, 2]$.

non-labor income allows one to hire more help to reduce the child care burden. Then, if wealthier workers employ more child care it would lead to a negative correlation between the time demands of children and non-labor income, which could compromise the validity of the instrumental variable. To evaluate this possibility, I test whether there is a relationship between the error term and spousal income by using the ATUS data. These results are reported in columns (2) and (5) of **Table 3**. Coefficients of spousal income in various specifications are not significantly different from zero.

Columns (3) and (6) of **Table 3** display regressions outcomes where all available instruments are used. The results of those specifications do not change the conclusion about the validity of instruments. Some studies show that TSTSLS estimator is asymptotically more efficient than the TSIV estimator, (see for example Inoue and Solon (2005)), therefore, in the first stage estimations I use education, spousal education and spousal income to instrument for maternity leave and change in hours.

SIPP data also offers a way to assess whether there is a correlation between education, non-labor income and child care demands. During the seventh Wave some of the respondents were asked whether they feel that their children are harder to care for than most children.[34] I test whether this variable is correlated with respondent's education and spousal income. Since the questions are very general and refer to all children I choose only respondents who had their first child during the survey course, but before Wave 7. The results are reported in **Table 4** and suggest that there is no significant correlation between education, spousal income and the hardship of taking care of children.

5.2.3 Results

The OLS and the second stage IV estimates measuring the depreciation rate of human capital are presented in **Table 5**. OLS measures the wage growth equation for new mothers as a function of maternity leave with and without substituting ratio of hours worked for the change in effort. OLS results are presented on the left panel of the Table. Column (1) presents the estimates of $\triangle \ln w_{it} = -\delta M_i + X_{it}\beta + \triangle \upsilon_{it}$, where change in effort is in the error term and column (2) shows the results for $\triangle \ln w_{it} = \sigma \ln \left[\frac{n_0(\Gamma-1)+1}{n_M(\Gamma-1)+(1-\overline{\eta})}\right] - \delta M + \beta X_{it} + \triangle \upsilon_i$, where $\overline{\eta}$ is the mean value of η_i measured in the ATUS data. The first term in the latter equation is a proxy for $\ln \left[\frac{n_0(\Gamma-1)+1}{n_M(\Gamma-1)+(1-\eta)}\right]$.

OLS results in **Table 5**, column (1), suggest that the monthly depreciation rate is 0.6 percent. The results in column (2) of the table show that the addition of the hours ratio, which partially accounts for the effort reallocation, positively affects the estimate of depreciation rate, which raises from 0.6 to 0.7 percent. This result implies that the portion of the change in effort which is captured by the proxy of hours ratio is positively correlated with the duration of maternity leave but is relatively small. As argued earlier in the paper, the coefficient of maternity leave in this regression might be biased if the duration of maternity leave is correlated with the remaining unobservable heterogeneity. The direction of the bias and its size depend on the distribution of time demands of children and on the value of effort demands of children. Without this information the direction of the bias cannot be determined.

TSLS estimation results are reported in columns (3) and (4) of **Table 5**. These results suggest

[34] "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.

that the OLS estimate of the monthly depreciation rate is downward biased (in absolute value). In column (3) I present the results of equation: $\triangle \ln w_i = \sigma \ln \left[\widehat{\frac{n_0(\Gamma-1)+1}{n_M(\Gamma-1)+(1-\eta)}}\right] - \delta\widehat{M} + X_{it}\beta + \triangle v_i$, where $\ln\left[\widehat{\frac{n_0(\Gamma-1)+1}{n_M(\Gamma-1)+(1-\eta)}}\right]$ is predicted using the coefficients obtained in first stage estimations using ATUS-CPS data (first stage results: **Table 2**, column 2) and $\widehat{M}$ is generated using the SIPP data. In these estimations standard errors of the structural coefficients are corrected for the fact that a predicted variable is used in the second stage. As a robustness check I also present the results obtained using the SIPP data in both first stage estimations (first stage results: **Table 2**, columns 5 and 6).[35] The second stage outcomes are displayed in column (4) of **Table 5**. Monthly depreciation rate estimates obtained in both specifications (using ATUS-CPS or SIPP) are very similar and are found to be between 1.1 and 1.2 percent.

TSLS outcomes reinforce the OLS results and suggest that longer maternity leave is associated with a bigger decrease in hourly wage. Both OLS and TSLS results show that the duration of maternity leave has a significant impact on wage loss. The depreciation rate is estimated to be around 0.7% in OLS estimations, and 1.1% employing the TSLS procedure. TSLS estimates of 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 order of 10-25% compared with continuously employed workers (Bartel and Borjas, 1981; Ruhm, 1987; Jacobson, LaLonde and Sullivan, 1993; Keane and Wolpin, 1997; for a survey, see Fallick, 1996). Mincer and Ofek (1980), using longitudinal panel data sample on married women in NSL, estimate that one year of non-participation results in 3.3 to 7.6 percent wage loss in the short run. Mincer and Polachek (1974), using a similar dataset, find that motherhood work interruptions lead to 4.3 percent annual wage loss for women with at least some college, (comparable to the mean of 14 years of schooling in the sample used in the current work).

The last two columns of **Table 5** report results obtained using alternative sets of instrumental variables. Both specifications were estimated using the SIPP data only. In column (5) I report the results that were obtained using spousal income and net worth record to instrument for the proxy of hours ratio and for the maternity leave duration. In column (6) I use state dummy variables to instrument (state indicators are expected to pick up information about regional labor market conditions, legislation and social norms). Monthly depreciation rates estimated in these specifications are very similar to (but less precise than) the ones obtained using the other specifications. (First stage estimations of the alternative specifications are reported in **Appendix Table 5**).

Comparison of OLS and IV Estimates If there is a positive relationship between the change in effort and the duration of maternity leave OLS would tend 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 longer out of the labor force after childbirth will also choose to work shorter hours after returning to the labor force and to exert more effort per hour of work. These allocations are feasible if child care is mostly time consuming and not energy consuming. If this is the case, a worker who spends fewer hours working at the market

[35] Please note that I obtain a similar estimate of the monthly depreciation rate by employing a first order approximation for $\left[\frac{n_0(\Gamma-1)+1}{n_M(\Gamma-1)+(1-\eta)}\right]$ instead of using $\left[\frac{n_0(\Gamma-1)+1}{n_M(\Gamma-1)+(1-\overline{\eta})}\right]$.

will be able to increase her effort inputs at all activities.

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

The final reason for the higher TSLS estimate is the existence of measurement error. Since maternity leave is a constructed variable the possibility of measurement error is not unlikely. This will cause the OLS estimates to be biased toward zero, but the IV results will be unaffected. Since most of the measurement error is expected to be concentrated at zero values of maternity leave, I repeat OLS and TSLS specifications where I include values of maternity leave above zero. The results from first and second stage estimations are reported in **Appendix Table 3** and **Appendix Table 4**, respectively. The coefficient estimates are not very different from those reported in **Table 2** and in **Table 5**, although the standard errors increase significantly. OLS results are still below those suggested by TSLS estimations, which implies that the suggested argument that longer maternity leave is associated with smaller decrease in effort is still valid.

5.2.4 Robustness Tests

In this subsection I validate the robustness of the results. I perform estimations for various segments of the new mothers population to evaluate whether the human capital depreciation rate varies across these specifications.[36]

Human Capital Depreciation and Education Many researchers put special emphasis on mothers' educational levels. 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 do not experience any penalty. Because the human capital accumulation process might be correlated education, I estimate TSLS and OLS regressions separately for high school graduates and dropouts and workers with more than high school education. To instrument for maternity leave duration and hours ratio I use alternative sets of instruments, spousal income, net worth record and state dummy variables. The results show that the depreciation rate does not vary much across educational levels.

Human Capital Depreciation and Occupational Choice Theoretical and empirical analysis presented in this work do not distinguish between general and firm specific human capital. The first type is transferable across firms, while the second type is lost when a worker decides to change jobs. In the current context, this distinction might have important economic consequences since workers who spent more time on maternity leave (more than 12 weeks) are not protected by the law[37] and are more likely to start a new job upon return to the labor force. This possibility raises the question of whether the results are driven by those workers who change jobs. On the other hand, occupational choice may reflect accommodating tighter time and energy constraints induced by child care requirements, this would imply that job mobility is endogenous and this is the reasoning not

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

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

to use indicators of job mobility as control variables. (Indeed, many researchers use industry and occupation choice to proxy for work effort exertion). I find that 28% of new mothers change jobs, compared to 11% in the control group. (The constructed variable whether or not returned to the same employer is comparable to the self-reported one in Wave 2, SIPP 1996 and 2001, where women were asked about their employment after the birth of their first child). To address the aspects of job mobility I perform OLS and TSLS estimations separately for job stayers, to test whether human capital depreciation rate for this group is different from the one obtained using the entire sample of new mothers. The results are reported in **Appendix Table 6**. OLS results are displayed in columns (1) and (2). Depreciation rates in these specifications is 0.6 - 0.7 percent, very similar to the values obtained using the entire sample. TSLS results for stayers are displayed in columns (3), are also not very different from the entire sample estimates, the point estimate of the monthly depreciation rate is 1.3 percent.

An additional aspect of occupational choice is in the context of the wage profile - human capital accumulation parameters may differ by occupation or industry. To address these issues, I test whether the depreciation rate varies by occupation. 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 represented occupations: professionals and managers, administrative support workers, sales workers and a merged category of laborers, personal and food service workers. For these estimations I use pre-motherhood occupations. I find that the estimated depreciation rate for the first two categories are slightly higher than the ones found for the whole sample. The estimates for the group of workers who were employed at sales positions or at low skill jobs are lower than those found for the entire population.

Additionally, I evaluate the effects of occupational choice on net accumulation rate of human capital. I perform these estimations using a subsample of continuously employed women who did not give birth during the sample period. I do not find any significant effect of occupations on net accumulation rate of human capital, the results are summarized in **Table 6**.

Selectivity Adjustment There is an additional potential bias that previous analysis cannot account for. The estimations require using 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, since data on the new wage are not available. Although the day of birth is random, some women give birth at the beginning of the survey and others towards the end, truncated spells might be correlated with longer unemployment spells. As a consequence, the rejection rule for truncated observations is non-random, since the long-term leaves are more likely to be removed from the sample. To correct for this selection, the conventional two-step selectivity adjustment procedure suggested by Heckman (1979) was implemented.

Selectivity adjusted results are reported in **Appendix Table 7**. In these estimations I assume that all explanatory variables are exogenous. Selection equations are reported in **Appendix Table 8**. First, I estimate a probit for the selection using all exogenous variables and an indicator for the random selection - the month of birth within the sample, exogenous by construction. In the third column I report the results obtained using additional instruments to control for the non-random selection. Overall, selectivity adjusted estimations show similar results to those obtained using the OLS specifications, which implies that the depreciation rate is not different for the truncated observations. Therefore, I do not perform selectivity adjustment corrections in the TSLS estimations. This outcome is consistent with the fact that the majority of women (90%, see Figure 2) return to the labor force within one year.

5.3 Step II: Evaluating the Effects Work Effort Reallocation

After obtaining the estimate for depreciation rate I proceed to the final step of the estimation. At this stage I compare wage changes of new mothers and non-mothers, before and after neutralizing the effect of human capital accumulation process. I respecify equation (19) in the following way:

$$\begin{cases} \Delta \ln w_{it} + \widehat{\delta} M = \sigma \Delta \ln f_{it} + \alpha M + X_{it}\beta + \Delta v_{it} & \text{if } Birth = 0\text{, new mothers,} \\ \Delta \ln w_{it} - \widehat{(\alpha - \delta)} M = \sigma \Delta \ln f_{it} + X_{it}\beta + \Delta v_{it}, & \text{if } Birth = 1\text{, non-mothers.} \end{cases} \quad (24)$$

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. Estimations performed at this stage should allow me to decompose the wage change disparity between new mothers and non-mothers into two channels: loss of human capital accumulation and mean change in work effort.

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

$$\Delta \ln w_{it} = (\alpha - \delta) M + X_{it}\beta + \Delta v_{it}, \quad (25)$$

The results are reported in **Table 6**. Monthly human capital accumulation is robust across various specifications and is found to be around 0.2 percent. (This implies that monthly accumulation rate - α, is 1.3 percent).

Then, the equation to estimate in the second stage is a modified version of equation (19) where change in wage is corrected by netting out the changes in human capital:

$$\Delta \ln \widehat{w}_{it} = Birth\, [\sigma \Delta \ln f_{it}] + X_{it}\beta + \Delta v_{it}, \quad (26)$$

where I assume that the change in effort of continuously employed women who did not have children is zero.

Given $\widehat{(\alpha - \delta)}$ and $\widehat{\delta}$ I can estimate equation (26). I evaluate the mean change in work effort of new mothers (scaled by the elasticity of effective market time with respect to effort exertion) by estimating the coefficient of childbirth indicator. The difference between coefficients of $Birth$ in equations (20) and (26) should provide an estimate for mean motherhood wage rate loss driven by the foregone human capital accumulation. I perform these estimations using the entire sample of women.

Estimation results of equation (26) are reported in **Table 7**. The first column reports the total wage growth disparity between new mothers and non-mothers, estimated using equation (20), I find that total motherhood wage penalty is around 6.5 percent. The estimation results of equation (26) are displayed in column (2) of **Table 7.** The coefficient of childbirth indicator is not significant, and its point estimate is relatively small. This result implies that, on average, forgone human capital accumulation while on maternity leave is the main reason for the wage growth gap between new mothers and women who did not have children during the survey period. The third column of **Table 7** reports decomposition results using the OLS estimate of monthly depreciation rate, $\delta = 0.6\%$. In this case almost one third of the maternity wage losses remains unexplained by changes in human capital, and would have been attributed to new mothers' energy reallocation channel. This result demonstrates that the correlation between change in effort and maternity leave duration is not trivial and appears to be notably important when explaining the motherhood wage penalty.

Note that the decomposition result does not imply that new mothers do not adjust their effort. However, it suggests that a woman who took an average length maternity leave will not change her hourly effort input after the return to the labor force. Moreover, on average, women who took shorter leaves return with lower work effort, while women with longer leaves return with higher work effort.

6 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. Little is known about the direction of these biases, and even less is known on their importance.

In this paper I correct for these biases and derive a new empirical evidence on the origins of wage losses associated with motherhood. The results suggest that, on average, child care is more time consuming than energy consuming. Workers who take an average-length maternity leave do not exhibit significant changes in their hourly effort input their return to the labor force. Their estimated wage losses are mainly driven by foregone human capital accumulation while on maternity leave, implying that the assertion that women with children exert lower levels of effort on the job is not well supported in the data.

I explore the link between the wage losses associated with motherhood and key factors often found in the literature in a dynamic model of human capital accumulation in a setting where labor force participation is endogenous and labor supply is measured by hours and effort. This framework is used to derive a series of implications which are utilized to construct an empirical decomposition strategy.

To evaluate each channel, I first net out selection issues by constructing wage growth using pre- and post-motherhood wage rates (wage growth equation for women who did not have children during the survey course is constructed around an arbitrary period). Then, I estimate the effects of the change in human capital on wage growth, these estimations yield measures of depreciation and accumulation rates of human capital. 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 course. I control for the correlation between unobservable energy reallocation and maternity leave duration by substituting for a portion of change in effort with a function of working hours before and after the 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.

Using longitudinal data from the Survey of Income and Program Participation (SIPP; 1996, 2001) the motherhood mean wage loss is estimated to be around 6.5%. I first estimate what portion of this gap is due to foregone human capital. For this analysis I draw data from SIPP, American Time Use Surveys and Current Population Surveys. I show that women who stay longer out of the labor force on maternity leave tend to earn lower hourly wages when they return to the market. Using the instrumental variables approach, monthly depreciation rate of human capital is estimated to be around 1.1%. This measure is underestimated in specifications that do not control for correlation between change in (unobservable) effort and maternity leave duration, this outcome could imply that this correlation is positive. In general, this would be the case if, on average, time demands of children were relatively more important than effort demands of children. This result also suggests that spending more time at home allows one to conserve energy and to increase effort exertion at all activities. I find that monthly net accumulation rate of human capital is around 0.2 percent. I further estimate that the failure to accumulate human capital while on leave explains more than 95% of the wage loss experienced by mothers, leaving little room for effort reallocation to explain the gap. The latter outcome implies that a woman who took an average length maternity leave will not change her hourly effort input after the return to the labor force, while a woman who took a longer than average leave is likely to provide an increased level of hourly effort upon return to the labor force.[38]

Theoretical and empirical implications of this paper open further lines of enquiry. One of the aspects that has not been investigated in this study is the public policy perspective. In my current research I further investigate the changes in labor supply associated with children, and examine how various public policies can affect market time and effort allocations following childbirth. I specifically examine how a change in maternity leave payments legislation would affect female workers' decisions and earnings. To address these questions I use a variation of the life cycle model developed in this work. I calibrate the model by matching simulated participation, hours and wage profiles to similar moments observed in the data. By combining empirical and theoretical results I will be able to derive conclusions about the effects of various public policy alternatives on motherhood wage losses.

[38] A support for these results can also be found in a non-scientific survey conducted by www.babycenter.com. This survey addressed the population of new mothers with a series of questions about their labor market outcomes upon return to the labor force. The survey reveals that out of about 600 respondends, only 12% replied that they input fewer hours and lower effort per hour, compared to their pre-birth labor supply. Of the respondents 40% reported that they increased their level of work effort, and 62% said that they experienced some depreciation of human capital upon return to the labor force.

I am greatful to www.babycenter.com, and especially to Marcella Bernhard Gates, for their interest and assistance with the survey. The poll can be found under the title: "Are you more or less efficient at work now that you're a mom?".

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7 Appendix

Theoretical Analysis - Characterization of the Optimal Conditions

I start by analysing the relationships between key parameters in the model and effective labor supply. Using implicit function theorem, it is possible to express consumption and effective labor supply as functions of the form:

$$c(t) = c\left[\lambda, \sigma, \rho, z, \eta, e, H_0, B, x(t)\right], \quad t = 0, 1, ..., \; T, \tag{A-1}$$

$$l(t) = l\left[\lambda, \sigma, \rho, z, \eta, e, H_0, B, x(t)\right], \quad t = 0, 1, ..., \; T, \tag{A-2}$$

where $l(t) = n(t)f(t)^{\gamma}$. Note, $H(t)$ is a function of H_0 and B. Substituting the $\lambda^{\star}$ constant consumption and effective labor supply functions into the budget constaint given by (5) yields the following equation

$$A_0 + \int_0^T e^{-rt}V(t)dt - \int_0^B e^{-rt}Fdt - \int_{B+M}^T e^{-rt}Fdt = \int_0^T e^{-rt}\left\{c\left[\lambda, \sigma, \rho, z, \eta, \phi, H_0, B\right]\right\}dt -$$
$$\int_0^B e^{-rt}\left[H(t)l\left[\lambda, \sigma, \rho, z, \eta, \phi, H_0, B\right]\right]dt - \int_{B+M}^T e^{-rt}\left[H(t)l\left[\lambda, \sigma, \rho, z, \eta, \phi, H_0, B\right]\right]dt, \tag{A-3}$$

This equation implicitly determines the optimal value of λ. λ, then, is a complicated function of initial assets, lifetime wages, interest rates, rates of time preference, consumers tastes, initial human capital level, age at childbirth and time and energy demands of children. In the absence of unexpected events, the worker continues on the same optimal path as selected at $t = 0$. Therefore, λ-constant consumption and effective labor supply functions fully characterize a consumer's dynamic behavior.

Concavity of preferences implies:

$$\frac{\partial \lambda}{\partial A_0} < 0, \; \frac{\partial \lambda}{\partial H_0} < 0, \; \frac{\partial \lambda}{\partial b(t)} < 0, \; \frac{\partial \lambda}{\partial F} > 0, \qquad t = 0, ..., T \tag{A-4}$$

and,

$$\frac{\partial \lambda}{\partial \eta} > 0, \; \frac{\partial \lambda}{\partial \phi} > 0. \tag{A-5}$$

Since λ is the marginal utility of lifetime wealth the results in equation (A-4) are an expected result, given that concavity implies diminishing marginal utility of income. Equation (A-5) holds since higher time and effort demands of children decrease the lifetime wealth.

From the assumption that consumption and effective leisure are normal goods and as a consequence of strict concavity of preferences, demand functions (A-1) and (A-2) satisfy the following properties, higher initial stocks of human capital or financial capital should increase the consumption of goods and leisure, summarized as

$$\frac{\partial c(t)}{\partial A_0} < 0, \ \frac{\partial l(t)}{\partial A_0} > 0, \frac{\partial c(t)}{\partial H_0} < 0, \ \frac{\partial l(t)}{\partial H_0} > 0, \frac{\partial c(t)}{\partial b(t)} < 0, \ \frac{\partial l(t)}{\partial b(t)} > 0, \frac{\partial c(t)}{\partial F} > 0, \ \frac{\partial l(t)}{\partial F} < 0,$$
$$t = 0, ..., T \tag{A-6}$$

Relationships between the demand function for consumption and effective leisure with time and effort demands of children is also straightforward. Tighter time and energy constraints reduce the lifetime wealth and therefore decrease the consumption and leisure, given that both are normal goods.

$$\frac{\partial c(t)}{\partial \eta} < 0, \ \frac{\partial c(t)}{\partial \phi} < 0, \frac{\partial \widetilde{l}(t)}{\partial \eta} < 0, \ \frac{\partial \widetilde{l}(t)}{\partial \phi} < 0, \qquad t = 0, ..., T \tag{A-7}$$

Since $\frac{\partial \widetilde{l}(t)}{\partial \eta} < 0$ and $\frac{\partial \widetilde{l}(t)}{\partial \phi} < 0$, an increase in demands of child care should be followed by an increase in effective labor supply "before", for $x(t) = 0$, while effective labor supply "after", when $x(t) = 1$, should be lower (provided that consumption is decreasing with demands of children). Then, workers with higher demands of children are expected to have a bigger drop in their effective labor, given by $l(t) = n(t)f(t)^{\sigma}$, following birth:

$$\frac{\partial \left(\frac{l_M}{l_0}\right)}{\partial \eta} < 0, \frac{\partial \left(\frac{l_M}{l_0}\right)}{\partial \phi} < 0, \tag{A-8}$$

where l_0 is the effective labor "before" and l_M represents effective labor "after",
and $\widetilde{l}(t) = \begin{cases} (1-n(t))\left(\frac{1-n(t)f(t)}{1-n(t)}\right)^{\sigma} & if \quad x(t) = 0 \\ (1-n(t)-\eta)\left(\frac{1-n(t)f(t)-\eta\phi}{1-n(t)-\eta}\right)^{\sigma} & if \quad x(t) = 1 \end{cases}$.

Next, I derive the relationships between the length of maternity leave and observable elements of λ. Fixed costs of work, either child care costs, commuting or other costs, are forgone while on leave and therefore increase the gain from staying out of the labor force. On the other hand, they also reduce the lifetime wealth and therefore the cost of being on leave increases. Higher level of human capital at time zero, H_0, is associated with higher forgone earnings, and therefore should reduce the time spent on leave, given the age at birth. It also increases the lifetime wealth and therefore may have a positive effect on the time spent on leave. Higher assets, a_0, and higher spousal income, $b(t)$, affect maternity leave decision through the wealth constraint by decreasing the marginal utility of lifetime wealth and have positive effects on the duration of maternity leave. Finally, the age at birth, B, affects the stream of income, and therefore affects the duration of maternity leave. Having children earlier parallels with being on leave while the level of human capital is relatively low, and therefore the depreciated amount of human capital is lower as well. In line with this reasoning, longer maternity leave should be more affordable for younger mothers.

Proposition 1 *The optimal maternity leave, M^*, and the change in exerted effort at work, $\frac{f_M}{f_0}$, are correlated.*

Proof. Given expressions (A-8) it must hold:

$$\frac{\partial\left(\frac{n_M}{n_0}\right)}{\partial\eta}\neq 0, \frac{\partial\left(\frac{n_M}{n_0}\right)}{\partial\phi}\neq 0, \frac{\partial\left(\frac{f_M}{f_0}\right)}{\partial\eta}\neq 0, \frac{\partial\left(\frac{f_M}{f_0}\right)}{\partial\phi}\neq 0, \tag{A-9}$$

Lets observe the labor force participation decision. The first order condition for the length of maternity leave, M, is

$$e^{-\theta M}\left(v\left[(1-\eta)\left(\frac{1-\eta\phi}{1-\eta}\right)^{\sigma}\right]-v\left[\widetilde{l}(B+M)\right]\right)\geq$$
$$\lambda H_0 e^{-\delta M}\left\{e^{(\delta-d-r)(B+M)}n(B+M)f^{\sigma}(B+M)+\int\limits_{B+M}^{T}e^{(\delta-d-r)t}n(t)f^{\sigma}(t)dt-e^{-r(B+M)}F\right\}, \tag{A-10}$$

where $\widetilde{l}(B+M)=(1-n(B+M)-\eta)\left(\frac{1-n(B+M)e(B+M)-\eta\phi}{1-n(B+M)-\eta}\right)^{\sigma}$.

The left-hand-side of the equation is the marginal cost of returning to work one period earlier since it is the sum of instantaneous gain in utility the agent receives from one period on leave and the fixed costs of work. The right-hand-side is the marginal benefit since it represents the gain in earnings the agent gets by working in moment M. The gain in earnings from shorter leave comes from two sources. First, the utility value of the additional earnings the agent get from working in moment M. Second, all earnings till time T are affected since while on leave there is no human capital accumulation.

First observe the left-hand-side of Equation (A-10), the marginal cost of returning to work one period earlier:

$$\left(v\left[(1-\eta)\left(\frac{1-\eta\phi}{1-\eta}\right)^{\sigma}\right]-v\left[\widetilde{l}(B+M)\right]\right)$$

$v(\cdot)$ is continuous and twice differentiable with $v\prime(\cdot)>0$ and $v''(\cdot)<0$. Therefore, $\forall\ n(B+M)>0$, $v\left[(1-\eta)\left(\frac{1-\eta\phi}{1-\eta}\right)^{\sigma}\right]>v\left[(1-n(B+M)-\eta)\left(\frac{1-n(B+M)f(B+M)-\eta\phi}{1-n(B+M)-\eta}\right)^{\sigma}\right]$. By concavity, $\forall\ \eta_1>\eta_2$,
$v\left[(1-\eta_1)\left(\frac{1-\eta_1\phi}{1-\eta_1}\right)^{\sigma}\right]-v\left[(1-n(B+M)-\eta_1)\left(\frac{1-n(B+M)f(B+M)-\eta_1\phi}{1-n(B+M)-\eta_1}\right)^{\sigma}\right]<$
$v\left[(1-\eta_2)\left(\frac{1-\eta_2\phi}{1-\eta_2}\right)^{\sigma}\right]-v\left[(1-n(B+M)-\eta_2)\left(\frac{1-n(B+M)f(B+M)-\eta_2\phi}{1-n(B+M)-\eta_2}\right)^{\sigma}\right]$.
And, $\forall\ \phi_1>\phi_2$, $v\left[(1-\eta)\left(\frac{1-\eta\phi_2}{1-\eta}\right)^{\sigma}\right]-v\left[(1-n(B+M)-\eta)\left(\frac{1-n(B+M)f(B+M)-\eta\phi_2}{1-n(B+M)-\eta}\right)^{\sigma}\right]<$
$v\left[(1-\eta)\left(\frac{1-\eta\phi_1}{1-\eta}\right)^{\sigma}\right]-v\left[(1-n(B+M)-\eta)\left(\frac{1-n(B+M)f(B+M)-\eta\phi_1}{1-n(B+M)-\eta}\right)^{\sigma}\right]$.
Therefore the marginal cost of returning to work one period earlier is increasing with the time and effort demands of children, η and ϕ.

The marginal benefit of earlier return to the labor force appears on the right-hand-side of

Equation (A-10):

$$\lambda H_0 e^{-\delta M}\left\{e^{(\delta-d-r)(B+M)}n(B+M)f^{\sigma}(B+M)+\int\limits_{B+M}^{T}e^{(\delta-d-r)t}n(t)f^{\sigma}(t)dt-e^{-r(B+M)}F\right\}, \tag{A-11}$$

higher time and effort demands of children are associated with higher λ, as in (A-5), and with lower post-birth effective labor, $l(t)$ for $t > B+M$, as shown in (A-8). In addition, there are no fixed costs while on leave, which should increase the benefit of not working. Then, the benefit of working is decreasing because lower effective labor supply is brought to the market, but it is increasing because the lifetime wealth is lower.

$$\left.\frac{\partial M}{\partial \eta}\right|_{\lambda} > 0, \left.\frac{\partial M}{\partial \phi}\right|_{\lambda} > 0$$

Then, since both the change in market energy inputs and the duration of maternity leave are correlated with the time and effort demands of children, the two decision variables are also correlated, and $\left.\frac{\partial M}{\partial\left(\frac{f_M}{f_0}\right)}\right|_{\lambda} \neq 0$. ■

Proposition 2 *$\exists\eta_1,\phi_1$ such that $\frac{f_M}{f_0} > 1$, and $\exists\eta_2,\phi_2$, such that $\frac{f_M}{f_0} < 1$.*

Proof. It follows from the first order conditions that

$$\frac{f_M}{f_0} = (1-\eta\phi)\frac{n_0\,(\Gamma-1)+1}{n_M\,(\Gamma-1)+(1-\eta)}. \tag{A-12}$$

$\frac{f_M}{f_0} \geq 1$ if $(1-\eta\phi)\frac{n_0(\Gamma-1)+1}{n_M(\Gamma-1)+(1-\eta)} \geq 1$ and $\frac{f_M}{f_0} < 1$ if $(1-\eta\phi)\frac{n_0(\Gamma-1)+1}{n_M(\Gamma-1)+(1-\eta)} < 1$. Then, $\frac{f_M}{f_0} \geq 1$ if $n_o(1-\eta\phi)-n_M \geq \frac{\eta(\phi-1)}{\Gamma-1}$ and $\frac{f_M}{f_0} < 1$ if $n_o(1-\eta\phi)-n_M < \frac{\eta(\phi-1)}{\Gamma-1}$. For the lower bound of ϕ, $\phi = 1$, we obtain: $\frac{f_M}{f_0} \geq 1$ if $\frac{n_0}{n_M} \geq \frac{1}{1-\eta}$ and $\frac{f_M}{f_0} < 1$ if $\frac{n_0}{n_M} < \frac{1}{1-\eta}$. For the upper bound of ϕ, $\phi \to \frac{1}{\eta}$, we obtain: $\frac{f_M}{f_0} \geq 1$ if $-n_M > \frac{1-\eta}{\Gamma-1}$ and $\frac{f_M}{f_0} < 1$ if $-n_M < \frac{1-\eta}{\Gamma-1}$. It is easy to see that for high values of ϕ the change in effort at work is negative. To conclude about the change in effort for the low values of ϕ, lets observe the following equation: $\frac{1-n_0}{1-\eta-n_M} = \left(\frac{f_M}{f_0}\right)^{\sigma}\frac{H_M}{H_0}\frac{u_2'(c_0,\widetilde{l}_0)}{u_2'(c_M,\widetilde{l}_M)}\frac{\widetilde{l}_0}{\widetilde{l}_M}$, which follows directly from the first order conditions. Where for simplicity I assume that $\delta = 0$, in the human capital accumulation function, and $u(c,\widetilde{l}) = \ln c + \ln \widetilde{l}$. Under those assumptions this equation simplifies to: $\frac{1-n_0}{1-\eta-n_M} = \left(\frac{f_M}{f_0}\right)^{\sigma}$. Then, $\frac{f_M}{f_0} \geq 1$ if $n_0 - n_M < \eta$, and $\frac{f_M}{f_0} < 1$ if $n_0 - n_M > \eta$. Since $\frac{n_0}{n_M} < \frac{1}{1-\eta}$ and $n_0 - n_M > \eta$ cannot hold simultaneously, it must hold that $\frac{f_M}{f_0} \geq 1$. Then for some values of η and ϕ $\frac{f_M}{f_0} > 1$, and there also exist values η and ϕ such that $\frac{f_M}{f_0} > 1$. ■

Table 1: Estimating the Family Gap, Effects of Childbirth on Wage Rates and Hours Worked

	Δln(w)	w_{after}	w_{before}	*Δln(w)*	*Δln(hours)*	$hours_{after}$	$hours_{before}$	*Δln(hours)*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Birth: [0, 1]	-0.0655	-0.0485	0.0159	-0.0201	-0.0948	-0.1291	0.0107	-0.0449
	(0.0137)	(0.0176)	(0.0163)	(0.0161)	(0.0139)	(0.0160)	(0.0140)	(0.0169)
Birth*Leave				-0.0087				-0.0093
				(0.0020)				(0.0030)
Leave				0.0022				-0.0011
				(0.0007)				(0.0005)
Education	0.0039	0.1057	0.1022	0.0032	-0.0008	0.0032	0.0060	-0.0017
	(0.0021)	(0.0031)	(0.0030)	(0.0021)	(0.0016)	(0.0021)	(0.0021)	(0.0016)
Age	-0.0301	0.0911	0.1208	-0.0336	0.0072	0.0211	0.0240	0.0027
	(0.0092)	(0.0112)	(0.0123)	(0.0092)	(0.0081)	(0.0099)	(0.0094)	(0.0081)
Age^2	0.0004	-0.0011	-0.0015	0.0005	-0.0001	-0.0003	-0.0003	0.0000
	(0.0001)	(0.0002)	(0.0002)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Black	0.0070	-0.0216	-0.0272	0.0093	0.0217	0.0868	0.0846	0.0230
	(0.0159)	(0.0216)	(0.0206)	(0.0159)	(0.0113)	(0.0125)	(0.0120)	(0.0114)
Metro	0.0092	0.1924	0.1820	0.0092	-0.0042	0.0005	0.0036	-0.0043
	(0.0104)	(0.0161)	(0.0157)	(0.0103)	(0.0091)	(0.0121)	(0.0119)	(0.0091)
# of children	0.0057	-0.0107	-0.0163	0.0061	-0.0033	-0.0455	-0.0584	-0.0020
	(0.0041)	(0.0063)	(0.0064)	(0.0041)	(0.0035)	(0.0048)	(0.0045)	(0.0035)
const	0.5393	-0.8237	-1.3570	0.6004	-0.1429	3.2372	3.1468	-0.0455
	(0.1569)	(0.1863)	(0.2030)	(0.1573)	(0.1417)	(0.1705)	(0.1607)	(0.1427)
N	5919	5919	5919	5919	5660	5660	5660	5660
r2	0.0080	0.2573	0.2601	0.0138	0.0233	0.0467	0.0398	0.0366

Note: Robust standard errors in parentheses.

Table 2: First Stage Estimations: "log(Hours Ratio)" and Maternity Leave on Education Variables, Spousal Income and TDI[1]

	ATUS-CPS					SIPP
	Hours Ratio: $\ln\frac{n_0(\Gamma-1)+1}{n_M(\Gamma-1)+1-\eta}$		Proxy for Hours Ratio: $\ln\frac{n_0(\Gamma-1)+1}{n_M(\Gamma-1)+1-\bar{\eta}}$			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. Income)	-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. Income)^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(spousal hours)^2.

Table 3: 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 Income)		0.0003	-0.0026		0.0096	0.0094
		(0.0131)	(0.0123)		(0.0065)	(0.0070)
Ln(Spousal Income)^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	0.03	0.0294	0.0330

	Children below 5 years old, N=499					
	Physical Child Care			Non-Physical Child Care		
	(1)	(2)	(3)	(4)	(5)	(6)
Ln(Spousal Income)	-0.0006		-0.0007	0.0019		0.0020
	(0.0027)		(0.0027)	(0.0018)		(0.0020)
Ln(Spousal Income)^2	-0.0019		-0.0020	-0.0025		-0.0024
	(0.0025)		(0.0024)	(0.0017)		(0.0017)
Mother's educ		0.0040	0.0005		0.0086	0.0077
		(0.0106)	(0.0100)		(0.0055)	(0.0061)
Father's educ		-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	0.02	0.0185	0.0219

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

Table 4: 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	0.02	0.02	0.02

[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 5: 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

[1] $\ln(Hours\ Ratio) = \ln \dfrac{n_0(\Gamma - 1) + 1}{n_M(\Gamma - 1) + 1 - \bar{\eta}}$

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

Table 6: Estimations of Net Accumulation Rate of Human Capital, Change in Log Wage as Dependent Variable, Non-Mothers Sample

	(1)	(2)	(3)	(4)
Leave[1]	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	4667	4667	4667	4667
r2	0.01	0.01	0.01	0.01

[1] The wage growth equation for the control group is constructed around an arbitrary period. Arbitrary period is randomly assigned using the percentage distribution of maternity leave of new mothers.

Note: Robust standard errors in parentheses.

Table 7: Estimating Motherhood Wage Loss with Adjusted Log Wage Change (α=0.2% and δ is as specified)

	All		
	Actual *Δln(w)*	**δ=1%**	**δ=0.6%**
	(1)	(2)	(3)
Birth	-0.0655	-0.0026	-0.0239
	(0.0137)	(0.0136)	(0.0136)
Education	0.0039	0.0029	0.0033
	(0.0021)	(0.0020)	(0.0020)
Age	-0.0301	-0.0354	-0.0333
	(0.0092)	(0.0092)	(0.0091)
Age^2	0.0004	0.0005	0.0005
	(0.0001)	(0.0001)	(0.0001)
Black	0.0070	0.0100	0.0091
	(0.0159)	(0.0159)	(0.0159)
Metro	0.0092	0.0092	0.0092
	(0.0104)	(0.0103)	(0.0103)
Children	0.0057	0.0065	0.0061
	(0.0041)	(0.0041)	(0.0041)
const	0.5393	0.6382	0.5954
	(0.1569)	(0.1572)	(0.1567)
N	5919	5919	5919
r2	0.0080	0.0046	0.0041

Note: Robust standard errors in parentheses.

Appendix Table 1: Summary Statistics, SIPP sample

	New Mothers, N=1252[1]		Non-Mothers, N=4667[1]	
	Mean	SD	Mean	SD
Hourly wage before	11.71	1.75	11.91	1.72
Hourly wage after	12.02	1.82	12.84	1.71
Hours before	35.29	1.5	35.32	1.45
Hours after	31.5	1.6	36.05	1.39
Leave	5.38	7.03	5.55	6.8
Education	14.33	2.5	13.98	2.26
Age	31.16	5.18	36.67	5.68
Black	0.07	0.25	0.09	0.29
Metro status	0.8	0.4	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	582.97	1.85	620.38	1.86
Spousal wage after	631.5	1.84	639.39	1.83
Spousal hours before	42.49	1.29	41.9	1.31
Spousal hours after	42.35	1.27	41.53	1.31
Changed industry	0.26	0.44	0.09	0.28
Changed occupation	0.28	0.45	0.11	0.32
Changed employer	0.36	0.48	0.15	0.38
Skilled workers[1]	0.73		0.76	
Unskilled workers[2]	0.27		0.24	

[1] Professionals, managers, technical workers, sales workers and administrative support workers

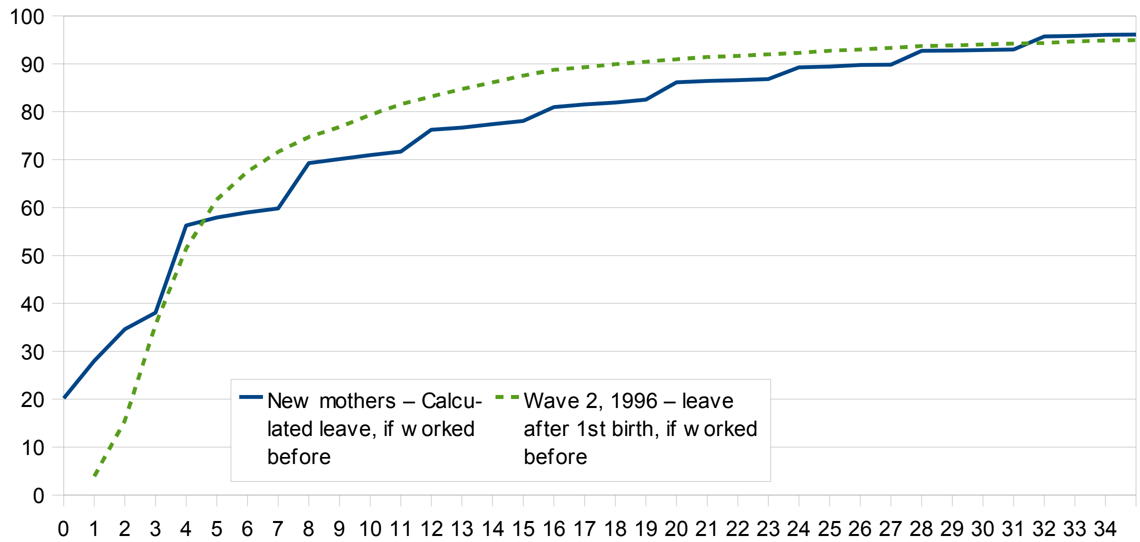
[2] Laborers, operatives, personal service, food service workers, etc.

Note: To measure hours before I use observations 12 months or more before childbirth. Therefore, statistics for hours before are calculated using 993 and 4667 observations respectively.

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

	ATUS-CPS, 1 child, weekdays		ATUS-CPS, 1 child, weekdays+weekends		ATUS, children below 2 years old		ATUS, children below 5 years old	
	N=150		N=277		N=395		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	1.4
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	10788	89	12973	75				
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	33.4	7.88	33.52	7.54
Black	0.04	0.2	0.03	0.18	0.05	0.21	0.05	0.21
Spousal hours after	37.35	2.3	36.33	2.42	36.2	2.91	36.48	2.96

Appendix Figure 1: Distribution of Maternity Leave[1]



[1] The percentage distribution obtained from Wave 2, 1996 is used to assign random spells to women who did not have children during the survey course.

Appendix Table 3: First Stage Estimations: "log(Hours Ratio)" on Education, Spousal Income and TDI dummy

	Maternity Leave		Proxy for Hours Ratio $\ln \frac{n_0(\Gamma-1)+1}{n_M(\Gamma-1)+1-\bar{\eta}}$	
	All	Leave>0	All	Leave>0
	(1)	(2)	(3)	(4)
Mother's educ	-0.5862	-0.5593	-0.0012	-0.0013
	0.0595	0.0695	0.0004	0.0004
Father's educ	0.0749	0.0932	0.0013	0.0008
	0.0604	0.0967	0.0005	0.0005
Ln(Sp. Income)	-2.2260	-1.2392	-0.0218	-0.0179
	1.4662	1.8905	0.0055	0.0075
Ln(Sp. Income)^2	0.2676	0.1465	0.0021	0.0018
	0.1209	0.1529	0.0005	0.0006
TDI	0.4346	-3.0021	-0.0033	-0.0057
	0.4668	0.5076	0.0016	0.0016
Metro status	-0.7033	-0.3878	0.0028	0.0039
	0.6089	0.6376	0.0014	0.0019
Age	-6.8051	-7.2116	0.0199	0.0273
	1.6344	1.4697	0.0049	0.0096
Ln(Sp. hours)	-7.8484	-4.2576	-0.0235	-0.0242
	4.3168	3.8401	0.0186	0.0210
# of children	0.4080	-0.2278	-0.0038	-0.0047
	0.3342	0.2966	0.0006	0.0007
const	104.4120	102.3320	-0.1204	-0.2019
	25.0998	22.9244	0.0717	0.1238
N	1252	845	1252	845
r2	0.0691	0.0892	0.0658	0.0585

Note: Robust standard errors in parentheses. Estimates include age^2, age^3, black [0,1], ln(spousal hours)^2.
TDI – Temporal Disability Insurance, state indicator.

Appendix Table 4: Evaluating Human Capital Depreciation Rate (δ): OLS & IV Estimates of the Log Hourly Wage Change Equation, "New Mothers" Maternity Leave > 0

	OLS		TSLS	
			1st stage – ATUS	1st stage – SIPP
	(1)	(2)	(3)	(4)
Maternity Leave (δ)	-0.0052	-0.0055	-0.0113	-0.0189
	(0.0019)	(0.0020)	(0.0081)	(0.0134)
Ln(Hours Ratio)[1]		0.4531	0.6494	7.5225
		(0.5834)	(0.9446)	(2.2469)
metro	-0.0126	-0.0146	-0.0477	-0.0363
	(0.0364)	(0.0359)	(0.0588)	(0.0233)
Age	-0.0942	-0.1050	-0.2844	-0.4826
	(0.1394)	(0.1411)	(0.2090)	(0.0830)
Black	0.0062	0.0107	0.0536	0.1133
	(0.0468)	(0.0468)	(0.0726)	(0.1184)
Ln(Sp. hours)	0.5003	0.5350	0.5896	-0.3752
	(0.4775)	(0.4824)	(0.4896)	(0.4869)
Ln(Sp. hours)^2	-0.0955	-0.1008	-0.1044	0.0280
	(0.0724)	(0.0728)	(0.0739)	(0.0670)
# of children	0.0263	0.0281	0.0255	0.0594
	(0.0163)	(0.0162)	(0.0165)	(0.0333)
const	0.8080	0.8691	2.6339	6.6586
	(1.6643)	(1.6922)	(2.2186)	(1.5937)
N	845	845	845	845

[1] $\ln(Hours\ Ratio) = \ln \frac{n_0(\Gamma - 1) + 1}{n_M(\Gamma - 1) + 1 - \bar{\eta}}$

Note: Robust standard errors in parentheses. Estimates include age2, age3.

Appendix Table 5: First Stage Estimations: “log(Hours Ratio)” and Maternity Leave on Net-Worth Record, Spousal Income and State Indicators

	$\ln\frac{n_0(\Gamma-1)+1}{n_M(\Gamma-1)+1-\bar{\eta}}$	Maternity Leave
	(1)	(2)
Ln(Sp. Income)	-0.0224	-2.5729
	(0.0051)	(1.8681)
Ln(Sp. Income)^2	0.0023	0.2720
	(0.0004)	(0.1532)
TDI	-0.0034	0.8660
	(0.0016)	(0.4467)
Net-worth record	0.0000*	0.0000*
	(0.2300)	-(2.2400)
Age	0.0182	-8.1508
	(0.0045)	(1.6777)
Black	-0.0073	2.1358
	(0.0031)	(0.9515)
Metro status	0.0024	-0.8617
	(0.0013)	(0.5159)
# of children	-0.0035	0.6454
	(0.0007)	(0.4018)
Ln(Sp. hours)	-0.0307	-7.2437
	(0.0193)	(3.8694)
Ln(Sp. hours)^2	0.0045	1.2779
	(0.0026)	(0.6468)
const	-0.0324	114.2592
	(0.0695)	(26.1969)
N	1220	1220
r2	0.0562	0.0528

* t-statistics in parentheses.

Note: Robust standard errors in parentheses. Estimates include age^2, age^3.
TDI – Temporal Disability Insurance, state indicator.

Appendix Table 6: Evaluating Human Capital Depreciation Rate (δ): OLS & IV Estimates of the Log Hourly Wage Change Equation, "New Mothers", Job Stayers

	OLS (1)	OLS (2)	TSLS (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.

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

[1] $$\ln(Hours\ Ratio) = \ln \frac{n_0(\Gamma - 1) + 1}{n_M(\Gamma - 1) + 1 - \bar{\eta}}$$

Note: Estimates include age^2, age^3.

Appendix Table 8: Selection Equations

	(1)	(2)
Maternity Leave (δ)	-0.0563	-0.0394
	(0.0086)	(0.0058)
Ln(Hours Ratio)	-1.6844	-0.6271
	(1.7076)	(1.6526)
Metro status	-0.1830	-0.1038
	(0.1590)	(0.1588)
Age	0.6619	0.1649
	(0.5287)	(0.5032)
Black	0.0602	-0.0663
	(0.2466)	(0.2395)
Ln(Sp. hours)	1.8565	1.2722
	(1.6419)	(1.6616)
Ln(Sp. hours)^2	-0.2986	-0.1929
	(0.2398)	(0.2528)
# of children	0.0253	-0.0383
	(0.0555)	(0.0598)
Month in sample	-0.0233	
	(0.0038)	
Mother's educ		0.0153
		(0.0340)
Father's educ		-0.0354
		(0.0331)
Ln(Spousal Income)		0.9618
		(0.5251)
Ln(Spousal Income)^2		-0.0931
		(0.0424)
cons	-7.7187	-4.6426
	(6.2054)	(5.9903)
athrho	0.0761	0.0415
	(0.0606)	(0.0618)
lnsigma	-0.9156	-0.9193
	(0.0355)	(0.0356)
N	1332	1332

Note: Estimates include age^2, age^3.