The Effect of Maternal Psychological Distress on Children's Cognitive Development*

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ABSTRACT: This paper investigates how maternal mental health, measured by psychological distress, affects family investments and shapes children's cognitive skills. I provide a model that incorporates ideas from both sociology and psychology into a fairly standard economic model of maternal investments. This model allows me to separate the different mechanisms that relate maternal mental health to children's cognition. In order to estimate the causal effect of mental health, I control for the endogeneity of mental health as well as the inherent measurement error in mental health constructs. For the former, I use variation among U.S. states in mental health insurance coverage laws. For the latter, I use an item response theory approach. Using a longitudinal data set from the U.S., the Panel Study of Income Dynamics (PSID) and its Child Development supplement (PSID-CDS), I find that maternal psychological distress mainly affects children through a decrease in the productivity (quality) of maternal time investments. My findings support two policy interventions that mitigate this effect. I find that mental health treatment for at-risk mothers can have significant payoffs for children and is significantly more cost effective than comparable income transfers. Moreover, I find that programs that improve maternal parenting can have large benefits for children of at-risk mothers.

KEYWORDS: HUMAN CAPITAL, CHILD DEVELOPMENT, MENTAL HEALTH.
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1 Introduction

There is a growing interest, in a multitude of fields, towards understanding intergenerational transmission of human capital. Studies have shown that inequality in family resources is translated into inequality in children's outcomes (Heckman and Mosso, 2014; Duncan, Kalil, and Ziol-Guest, 2013; Currie and Almond, 2011; Alexander, Entwisle, and Olson, 2014). Moreover, we now know that at least half of the variation in lifetime earnings is determined in childhood (Cunha, Heckman, and Navarro, 2005). Many factors have been shown to explain the transmission of poverty, including for example genetic endowments or the number of words spoken to the child in infancy. These results are often discouraging as many of these factors are not easy policy targets. This is not the case for maternal mental health, which has been shown to be highly correlated with both socioeconomic status and child outcomes (Cogill et al., 1986; Caplan et al., 1989) and proven to be malleable through policy (Earls et al., 2010; Evans and Garthwaite, 2014). However, maternal mental health has been understudied in Economics and as a result we know very little about the mechanisms through which it affects child outcomes.

The objective of this paper is to evaluate the mechanisms that explain the effect of maternal mental health on children's cognitive development. I build on many strands of the child development literature to describe the different mechanisms that relate maternal mental health to children's cognitive development. In order to estimate these different mechanisms, I estimate policy functions for different maternal investments jointly with the child's technology of skill formation. This approach allows me to assess the effect of maternal mental health on the quantity as well as on the productivity (quality) of maternal investments. I use variation in parity laws that determine mental health care access and coverage across states to estimate the causal effect of maternal mental health.

I find that maternal mental health matters for children's development. Moreover, I find that maternal psychological distress mainly affects children through a decrease in the productivity (quality) of maternal time investments. Next, I investigate policy interventions that mitigate these effects. I find evidence of large payoffs for children from mental health treatment for at-risk mothers. I also find evidence that programs that improve maternal parenting can have large benefits for these children. Moreover, both policies are significantly more cost effective than comparable income transfers.

Different fields use different models to understand human capital formation in children. I bring together these different models by incorporating maternal mental health into a standard economic model of maternal investments. Economists understand child development through the family investment model (Becker, 1981; Becker and Tomes, 1986). In this model, parents influence children through biological endowments (genetics) and social endowments (values) as well as through time and monetary investments. In this basic framework there are at least five mechanisms that explain why maternal mental health can have an effect on children. The first mechanism comes from the idea in psychology that mental illness can be contagious, so children of distressed mothers are more likely to develop mental health problems of their own, which would impair their cognitive development (Rosenquist, Fowler, and Christakis, 2011; Currie and Stabile, 2006). The second mechanism is the idea from the family stress model in sociology that maternal mental health problems can affect the quality of mother-child interactions as it diminishes the mother's ability to be supportive and engaged with her child (McLoyd, 1990; Conger et al., 1994; Yeung, Linver, and Brooks-Gunn, 2002). The third and forth mechanisms come from the idea in psychology that mental health problems can increase the cost of spending time in productive activities, and as a result can affect the amount of time the mother spends with her child as well as her labor force participation (Blair, 2010; Frijters, Johnston, and Shields, 2014). The last mechanism come from the economics literature, which has shown that mental health problems could lead to lower labor market productivity (Chatterji, Alegria, and Takeuchi, 2011). In turn, lower earnings could translate into lower monetary investments in children.

Identifying these mechanisms is important for policy, as different mechanisms point towards different policy proposals. For example, if mental health affects the quality of maternal parenting, home visitation programs that improve the quality of mother-child interactions might be highly beneficial for children of mothers in poor mental health. Alternatively, if the effect is through a change in the mother's labor market productivity, then income supplement programs such as the earned income tax credit (EITC) might be important for these families. Identifying these mechanisms can also highlight heterogeneous effects of mental health treatment across families. For example, the benefits of treatment will be higher for children of working mothers if the mental health effect is through the mother's labor market productivity, and possibly larger for stay-at-home mothers if the effect comes through the quality of mother-child interactions.

In estimating the causal effect of maternal distress, I confront two empirical challenges: measurement error in the mental health construct and the endogeneity of mental health. In order to control for the measurement error problem, I use an item response theory (IRT) model. IRT is a common method in psychology used to identify and construct unobservable scales from a series of discrete measurements. Mental health scales, including the Kessler 6 psychological distress scale that I use in this paper, are constructed from multiple self-reported discrete responses about different psychological symptoms. The IRT approach recognizes and controls for the intrinsic measurement error in these self-reported questionnaires.

Moreover, it controls for the fact that measurements differ in quality, each providing a different signal about the unobserved mental health. I find that not controlling for these problems, and instead using a simple summation score, leads to biased and unreliable estimates.

In order to address the endogeneity of maternal mental health, I use variation in state mental health parity laws. These laws require insurers in the state to provide an equal level of benefits for mental illness and physical disorders. [1] These laws are generally thought to improve access to mental health services in the state, and have been shown to increase utilization of mental health care services and contribute to improve mental health outcomes (Harris, Carpenter, and Bao, 2006; Lang, 2013). In theory, these laws only enter the model through an effect on the mother's mental health and as a result serve as exclusion restrictions that identify the model. Otherwise, I would not be able to identify the causal effect of the mother's mental health, as it is possibly correlated with unobservable investments in children. [2] [3] The literature has struggled to correct for this problem often relying on poor instruments, bounding or propensity score methods (see Frank and Meara (2009) and Dahlen (2016) as examples). Exceptions are papers that use exogenous variation in stressors that could trigger mental health illness, such as terrorist attacks (Camacho, 2008) or the death of a relative or close friend (Persson and Rossin-Slater, 2014; Frijters, Johnston, and Shields, 2014). [4]

My findings show that maternal mental health, measured by mothers' psychological distress, has large effects on children's cognitive development. The main mechanism explaining these large effects is the effect of maternal mental health on the returns of maternal time investments (quality of mother-child interactions). This channel alone explains 70% of the effect of maternal distress on children. I also find evidence of a direct effect of maternal distress on children's cognitive development, possibly explained by the contagion of mental health. I find no evidence of the other mechanisms once I control for measurement error and endogeneity of maternal distress. These findings point towards two policy interventions for children of psychologically distressed mothers. The first is mental health treatment, either with therapy or medication. I find that treatment for at-risk mothers can have huge payoffs for children are 16 times more cost effective than comparable income transfers. The second policy would be to improve the quality of mother-child interactions, as in ,for example, home visitation programs. Policies that improve maternal parenting reduce the negative

[1] These benefits include visit limits, deductibles, copayments, and lifetime and annual limits.

[2] For example, I do not observe neighborhood characteristics, such as the crime rate or school quality, that we know are important for children's development.

[3] Another problem is reverse causation. At the same time that maternal mental health can influence labor market and child outcomes, lack of financial resources and poor child outcomes can lead to maternal mental health problems (Dohrenwend et al., 1992).

[4] One issue with these instruments, when studying postpartum mental health, is that they can directly influence children and as a result would not be valid exclusion restrictions.

effect of maternal distress on the returns of maternal time investments, and as a result produce large benefits for children of distressed mothers. These programs can be thought as complementarity to mental health treatment and a viable option when treatment does not work.

The remainder of the paper proceeds as follows. In Section 2, I describe the data and my measure of mental health. In Section 3, I describe the conceptual model of maternal investments and highlight the different mechanisms through which maternal mental health can influence children's development. In Section 4, I describe my econometric framework and estimation strategy. In Section 5, I describe my main findings. In Section 6, I discuss the policy implications of these findings. Section 7 concludes.

2 Data and Preliminary Analysis

In this section, I first provide details on the data used and on how I construct the analytic sample. Then, I discuss my measure of mental health and provide background information on the measure that might be informative for some readers. Lastly, I report estimates from a preliminary econometric model relating maternal mental health with child cognition and maternal investments. In particular, I demonstrate that maternal distress is negatively correlated with both child cognition and other relevant maternal investments.

2.1 The Panel Study of Income Dynamics

In this paper, I use data from the *Panel Study of Income Dynamics* (PSID) and its *Child Development Supplement* (CDS). The PSID is an ongoing dynastic longitudinal survey. It started as a nationally representative sample of 18,000 individuals living in 5,000 families in 1968 in the United States. The CDS collected information on 3,563 children living in 2,394 PSID families. Information was collected in three waves: 1997, 2002 and 2007. Eligible children were between the ages of 0 and 12 in 1997, at the time of the first survey. These surveys include a broad array of developmental outcomes as well as information on the home environment of the child. The PSID-CDS is particularly well-suited for this study since it provides information about mothers' mental health together with information about the quantity of mother-child interactions and mothers' labor market outcomes. Therefore, the data set allows me to relate the mother's mental health to maternal investments in the child.

From the main PSID survey, I collect data on mothers' labor supply decision, labor income, total family income and relevant demographic variables from the year the child was born until she reaches 16 years old. This data collection goes as far as 1985 and as recent as 2013. From the CDS, I collect information on the child's cognitive ability, on the mother's mental health and on the mother's time with the child. This data is collected from the three CDS surveys in 1997, 2002 and 2007. In constructing my analytic sample, I keep respondents with valid information on the child's cognitive test score, mother's labor supply, mental health and time with her child. I drop individuals with missing information on the child's race, gender, birth-order, as well as those with missing information on the mother's education and age at the child's birth. The resulting analytic sample has information on 2,459 children and their mothers.

I measure the child's cognitive development with the Letter-Word (LW) module of the Woodcock-Johnson aptitude test. The Letter-Word Identification test assesses symbolic learning and reading identification skills. The test is ideal as it can be administered to children between the ages of 3 and 17 and as a result most children were eligible for the test in two CDS surveys.

I use the child's time diary to measure the time the mother spends with her child. This is a distinctive feature of the PSID-CDS. The CDS asks participant children, or their primary caregivers, to record a detailed, minute by minute timeline of their activities for two days of the week: one random weekday and one random weekend day. Activities were coded at a fine level of detail. From this data, I construct a measure of maternal time investments by taking a weighted sum ($\frac{5}{7}$ for the weekday and $\frac{2}{7}$ for the weekend) of the total hours in which the mother is recorded as **actively participating** with the child in each diary activity. Active participation can be thought of as a measure of maternal engagement with the child.

2.2 Psychological Distress

I use the *Kessler 6 (K6) Psychological Distress Scale* (Kessler et al., 2002) to measure the mother's mental health. The K6 scale is a simple and widely used measure of general psychological distress. [5] Psychological distress is largely defined as a state of emotional suffering characterized by symptoms of depression (e.g. lost interest, sadness, hopelessness) and anxiety (e.g. restlessness, feeling tense) (Mirowsky and Ross, 2003; Drapeau, Marchand, and Beaulieu-Prévost, 2011).

The K6 scale involves asking 6 questions about the individual's emotional state in the previous four weeks. Each individual is asked 'in the last 4 weeks, about how often did you feel': 1) nervous, 2) hopeless, 3) that everything was an effort, 4) so sad that nothing could

[5] Other scales have also been developed with the intent to measure psychological distress. Other examples are the General Health Questionnaire (GHQ), the Kessler K10 scale and the Brief Symptom Inventory (BSI).

cheer you up, 5) worthless, and 6) restless or fidgety. Each question is scored on a scale of five values (0-4), where 4 indicated "All of the time" and 0 indicated "None of the time". [6].

The prevalence rate of psychological distress is non-trivial for the U.S. adult population. Psychological distress is usually measured on a continuous scale, but more often than not individuals are classified into three groups: those suffering from moderate psychological distress, those suffering from serious psychological distress, and those under no distress. Moderate levels of distress are very common, with a prevalence rate of 20-30% for the U.S. adult population. [7] Serious psychological distress is much rarer, with a prevalence rate of about 3% for the U.S. population.

In spite of being quite common, psychological distress can lead to serious life impairments. Individuals in serious distress report lower productivity in the home and in the labor market, and problems in interactions with friends and family members. Individuals with moderate levels of distress suffer similar impairments but at a lesser rate. For instance, 85% of individuals under serious distress report facing some work impairment, while about 60% of individuals under moderate distress report the same (Prochaska et al., 2012).

The prevalence of psychological distress is fairly constant across geographical regions, but there are important group differences (Drapeau, Marchand, and Beaulieu-Prévost, 2011). In particular, the prevalence of psychological distress is higher for women than for men, and peaks during early adulthood (18-29 years old). [8]

2.3 Summary Statistics

In this section, I discuss the most important patterns in the data. I first demonstrate that both child cognition and maternal distress are highly correlated with family income, a result that motivates this paper. Next, I describe the other key variables: the mother's time investments in the child, hours of work and her wage offer.

This paper is motivated by the fact that maternal mental health is strongly correlated with both socioeconomic status and child cognition and, as a result, can be thought of

[6] I use a simple item response theory (IRT) approach to construct a continuous and measurement-error-free scale from the six responses. I discuss this approach in detail in Section 4.4 In comparison, the usual approach is to sum the scores on the six questions and use cut points to separate individuals in three levels of distress. As a general rule, a cut point of 13+ is used as the optimal cut point for assessing the prevalence of serious mental disorder in the national population (Kessler et al., 2010). A cut point between 5 and 8 can also be used to indicate a moderate mental disorder (Prochaska et al., 2012; Herrick, 2015). This separation is often used to analyze the prevalence rate of psychological distress in the population.

[7] These numbers depend on the cut-off being used.

[8] Also, there are no significant differences in prevalence across races or ethnic groups, but the prevalence is higher for immigrants (Nemeroff, Midlarsky, and Meyer, 2010; Drapeau, Marchand, and Beaulieu-Prévost, 2011).

as a mediator of the intergenerational transmission of human capital. Figure 1(a) plots the association between psychological distress and family income. The pattern is striking. Individuals in the lower end of the income distribution face much higher levels of distress (1 s.d. higher) than individuals with high levels of income. Moreover, this negative relationship is stronger at lower levels of income, suggesting that psychological distress is strongly related to financial strain and poverty. [9]

Similarly, child cognition is also highly correlated with family income. This can be seen in Figure 2(a), which plots average standardized letter-word score for different percentiles of family income. This gap in cognitive skills can be as large as one standard deviation. Moreover, this gap tends to grow over time, as can be seen in Figure 2(b). The gap doubles from .6 to 1.2 points of a standard deviation from age 3 to age 15. One of the goals of this paper is to explore the role of maternal mental health in explaining this gap.

Besides maternal mental health, family time and goods investments can also explain this gap and, as a result, are part of my model. Table 1 provides summary statistics on these variables. On average, mothers spend 19 hours per week engaged in activities with their children. However, as can be seen in Figure 3(b), there is large variation in time investments across child ages. Mothers spend more than double the amount of time with young children than with teenagers. Similar patterns can be found for maternal labor force participation. On average, mothers spend 1,209 hours working every year; their labor force participation is lower in the first years of the child's life and increases steadily as the child ages, as can be seen in Figure 3(c). Perhaps due to human capital accumulation and depreciation through work experience, mothers' wages decrease when children are young, when mothers take time off from the labor market, and increase steadily over time, as mothers accumulate labor market experience. This can be seen in Figure 3(d).

One important thing to notice in Table 1 is that I do not observe all variables at all ages for each child. For example, I only observe the letter-word score for 4,582 child-age observations, close to two observations per children. Similarly, I only observe 25,795 observations for mothers' labor force participation, about 10 observations per mother. However, I do observe these same variables at all ages for at least some children, as can be seen in Figures 3(a)-3(d). As a result, I can construct moments that will allow me to estimate the model proposed in the next two sections. That is, these patterns in the data motivate the method of simulated moments estimation approach described in detail in Section 4.5.

[9] Figure 1(b) plots the density distribution of psychological distress for the mothers in my sample. There is a very clear clustering of scores around zero. This is due to the fact that in my sample about 15% of the mothers respond "none of the time" to all 6 questions in the K6 scale. As a contrast, only 6% of the individuals respond "all of the time" to *any* question and only 4 individuals respond "all of the time" in all 6 questions.

2.4 Preliminary Results

In my main econometric analysis, I control for endogeneity of maternal mental health using variation in state mental health parity laws. Moreover, I simulate maternal investments and jointly estimate these with the child's cognition production function. However, for the preliminary analysis conducted here, I assume maternal mental health is exogenous and explore its correlation with child cognitive development and its correlation with other relevant maternal investments. These preliminary results serve to illustrate important patterns in the data and to demonstrate that my main results are not driven by my estimation strategy.

I start by estimating a static model of children's cognitive development. The main outcome of interest are age-standardized logged letter-word scores. I estimate OLS regressions of the following form:

$$log(A_{it+5}) = log(H_{it})\phi_1^H + log(MT_{it})\phi_1^M + log(Inc_{it})\phi_1^I + X_{i1}\phi_1^X + \epsilon_{i1} \tag{1}$$

where the letter word score for individual i at time t is given by A_{it}, and H_{it}, MT_{it}, Inc_{it} refers to the mother's psychological distress, maternal time investments and family income respectively. X_{i1} is a vector of covariates and ϵ_{i1} is a normally distributed disturbance. [10]

Estimates for equation 1 are presented in Table 2 for varying sets of covariates X_{i1} and family investments. Column [1] displays the raw relationship between maternal psychological distress and children's cognition. A ten percent increase in maternal psychological distress is related to a decrease of about 1.2 percentage points in children's cognitive skills. This relationship is also plotted in Figure 4(a). In column [2], I add family controls, such as the mother's education. Including these controls decreases the magnitude of the association with maternal psychological distress by about a half. This illustrates the strong endogeneity problem due to unobserved investments. In column [3] and [4], I include my measure of maternal time investments and family income respectively. Including these variables further decreases the magnitude of the association with the mother's distress by about 10%. In the end, it looks that maternal mental health is 70% as important in determining child cognition as family income. These results, however, should be taken as correlations since they assume investments are exogenous and ignore the dynamic nature of child development.

Given that time and goods investments are important determinants of children's skills, I would like to understand the correlation of maternal distress with the determinants of these

[10] I use children's scores at $t + 5$ in order to capture the idea that today's investments determine future cognitive skills. The analysis with cognitive scores measured at t yield qualitatively similar results.

investments. In order to do so, I estimate OLS regressions of the following form:

$$Y_{it} = log(H_{it})\phi_2^H + X_{i2}\phi_2^X + \epsilon_{i2} \tag{2}$$

where Y_{it} measures weekly maternal time investments, annual hours at work or log hourly wages for individual i at time t. As before, H_{it} refers to the mother's psychological distress, X_{i2} is a vector of covariates and ϵ_{i2} is a normally distributed disturbance.

Estimates for equation 2 are presented in Table 3 for varying sets of covariates X_i. Figure 4 also plots the relationship between family investments and psychological distress using linear polynomials. Column [1] displays the raw relationship between maternal psychological distress and weekly maternal time investments. Each percent decrease in maternal psychological distress is related to an increase of 0.825 hours in maternal time investments. These are relatively large associations as can be seen in Figure 4(b). However, this relationship decreases by a third when I add family controls, such as the mother's education (Column [2]). Similar effects can be seen for the effect of distress on the mother's labor supply (Columns [3] and [4] and Figure 4(c)). Each percentage increase in maternal distress is associated with a decrease of about 40 hours worked in a year. Perhaps related, psychological distress is also strongly correlated to labor market productivity. As can be seen in Columns [5] and [6] and Figure 4(d), a ten percentage increase in psychological distress is associated with a five percentage decrease in hourly wages.

The results in Tables 2 and 3 and Figure 4 provide preliminary evidence that maternal mental health matters for children's cognitive development. Moreover, they provide suggestive evidence that maternal mental health can affect children through its effect on other family investments. However, these results have several shortcomings. They do not control for endogeneity in the child cognition production function as a result of unobserved investments (omitted variable bias). Moreover, they ignore the fact that child development is a dynamic process and that investments interact in non-obvious ways in determining child outcomes. The model developed in the next couple of sections takes these issues seriously. Moreover, it formally describes the different channels through which maternal mental health can affect children.

3 A Model of Cognitive Skills Formation

In this section, I describe a standard model of maternal investments in children's cognitive development. This model allows me to distinguish the channels through which maternal mental health can affect children. I start by describing the technology of cognitive skill formation in children. I argue that the child's cognitive skills are determined over multiple periods by mother's time and goods investments as well as by the mother's mental health. I then discuss the determinants of these maternal investments. I show that maternal time and goods investments are determined by the mother's preferences, the constraints she faces and her productivity in the labor market, and that maternal mental health can affect these investments. At the end of this section, I comment in some detail on the different channels through which maternal mental health can influence the child's cognitive skills formation. Throughout this section, I treat mental health as exogenous and address the endogeneity problem later, in Section 4.3.

Before I describe the model, I should mention that I will not fully estimate the model proposed in this section. Instead, I will use the ideas developed in this section to motivate the empirical model described in Section 4. More specifically, I will approximate the maternal time allocation decisions with policy functions and estimate these jointly with the child's technology of skill formation and the mother's wage offer, where the technology of skill formation is estimated in its structural form. In Section 4, I will argue that this approach provides some advantages over fully structural estimation and that this approach is closely related to what has been done in the literature (see Cunha, Heckman, and Schennach (2010) and Agostinelli and Wiswall (2016) for two examples).

3.1 Cognitive Skill Formation

Child cognition is determined over multiple periods ($t \in \{0, 1, ..., 16\}$). Each period is equivalent to a year in the child's life. The model starts when the child is born ($t = 0$) and ends when she reaches age 16 and can leave the household. The child's stock of cognitive skills (A_t) is determined at the beginning of every period. In the initial period, the child is born with an initial ability stock (A_0), which is determined by genetic and in-utero investments. At each subsequent period, the mother determines her child's skill evolution by allocating time (MT_t) and goods investments (G_t) for the child. This is a common assumption in the literature (see Becker and Tomes (1986) as an early example). Expanding on the literature, I also allow the mother's mental health (H_t) to influence the child's accumulation of skills. Formally, the child's skills evolve as follows:

$$A_{t+1} = f_t(A_t, G_t, MT_t, H_t, \eta_t) \tag{3}$$

where η_t captures shocks and unobserved inputs that affect the child's development. The technology $f_t(\cdot)$ is allowed to change as the child ages in order to capture different stages of development.

The specification of the technology of skill formation ($f_t(\cdot)$) should take into account two important features of child development: dynamic and static complementarities of investments. Dynamic complementarity suggests that the returns to current investments depend on the child's current ability ($\frac{\partial^2 A_{t+1}}{\partial A_t \partial I_t} \neq 0$). As a result, returns to current investments will depend on past investments in the child ($\frac{\partial^2 A_{t+1}}{\partial I_{t-1} \partial I_t} \neq 0$) (see (Cunha and Heckman, 2007) for a thorough discussion). Moreover, static complementarity suggests that the technology should allow for the returns to current investments to depend on other investments, e.g. $\frac{\partial^2 A_{t+1}}{\partial MT_t \partial H_t} \neq 0$. This second feature is especially important when incorporating maternal mental health.

Maternal mental health can enter the human capital production function in two ways. First, maternal mental health can be thought as a 'direct' component of the child's human capital production function in the same way as financial investments or maternal time investments. One explanation is that children suffer from their parents' psychological distress and in turn develop psychological problems of their own (Rosenquist, Fowler, and Christakis, 2011; Eisenberg et al., 2013; Ross, 2000). In turn, psychological problems inhibit children's cognitive functions such as planning and attention leading to further developmental problems (Blair, 2010; Blair et al., 2011). Second, maternal mental health can influence the productivity of maternal time investments. The idea comes from the family stress theory in sociology, which proposes that maternal psychological distress can provoke harsh, inconsistent and low nurturing parenting (Conger et al., 1994, 2002). In a sense, the idea is that the mother's mental health is an important determinant of the quality of maternal time investments. The technology of skill formation should take into account these two different mechanisms.

In order to accommodate these features, I assume the technology of skill formation follows the translog (transcendental logarithmic) specification. Perhaps the most obvious approach would be to follow Cunha, Heckman, and Schennach (2010) and assume child development is described by a CES production function. The CES is appealing because it contains both the Leontief and the Cobb-Douglas functions in the limit as the complementarity parameter approaches $-\infty$ or 0. Moreover, the CES specification allows mental health to have a 'direct' effect on children's development. It also allows for maternal time investments and mental health investments to be complements in the child's human capital production function. However, the CES is problematic because it assumes identical elasticities of substitution between all input factors. This restriction is limiting as it does not allow me to estimate the separate effect of the mother's mental health on the productivity of her time with the child. On the other hand, the translog allows me to do just that. [11] Using the translog specification, I write the technology of skill formation as:

$$\begin{aligned} ln(A_{t+1}) = & \; ln(K_t) + \alpha_{1t} ln(A_t) + \alpha_{2t} ln(G_t) + \alpha_{3t} ln(MT_t) + \alpha_{4t} ln(H_t) \\ & + \alpha_{5t} ln(A_t) \times ln(G_t) + \alpha_{6t} ln(A_t) \times ln(MT_t) + \alpha_{7t} ln(A_t) \times ln(H_t) \\ & + \alpha_{8t} ln(G_t) \times ln(MT_t) + \alpha_{9t} ln(G_t) \times ln(H_t) \\ & + \alpha_{10t} ln(MT_t) \times ln(H_t) + \eta_t^a \end{aligned} \tag{4}$$

where K_t corresponds to the total factor productivity of investments.

The translog is a generalization of the Cobb-Douglas, which is the special case where the interaction parameters are all zero ($\alpha_{jt} = 0 \, \forall j \in \{5, 10\}$). These same interaction parameters allow for non-constant elasticity of substitution between inputs, which is not allowed in the Cobb-Douglas, and for different partial elasticities of substitution between inputs, which are restricted in the CES. [12] α_{5t},α_{6t} and α_{7t} capture the degree dynamic complementarity (beyond the one implied by the Cobb-Douglas), where early investments are allowed to influence the returns of today's investments (Cunha, Heckman, and Schennach, 2010; Aizer and Cunha, 2012). For example, $\alpha_{5t} \geqslant 0$ implies that $\frac{\partial^2 A_{t+1}}{\partial A_t \partial G_t} \geqslant 0$. [13] Similarly, α_{10t} describes the elasticity of substitution between maternal mental health and maternal time investments. If $\alpha_{10t} = 0$ the elasticity of substitution between maternal mental health and maternal time investments equals the one implied by the Cobb-Douglas specification.

It is also important to note that all parameters are subscripted by t. Following (Cunha, Heckman, and Schennach, 2010), I assume there are two stages of development, ages 0-5 and ages 6-16. There are many reasons for this distinction. For one, at age 6, the child enters formal schooling and as a result is no longer exposed to only the home environment. Also, the interpretation of the returns of maternal time changes at age 6. Both the types of activities the mother engages with the child and the types of activities the child engages without the mother changes once the child enters formal schooling. As a result, we should expect the return of maternal time to be different across developmental stages. The same is true for the other investments.

Since the child initial ability A_0 is unobserved, I also need to make some assumptions on

[11] Another alternative is a Nested CES production function. In a Nested CES two inputs, maternal mental health and time investments, are combined in a CES production function, which is then nested in a further CES production function which includes goods investments and the child's original human capital. I find qualitative similar results when I use a Nested CES production function.

[12] The translog function could be expanded to include additional terms to provide an approximation to any unknown production technology.

[13] The Cobb-Douglas imposes dynamic complementarity of investments, so even if $\alpha_{5t} < 0$ it is possible for dynamic complementarity to be present.

how it is realized. I assume A_0 is a function of the mother's and child's observed characteristics at the child's birth (X_0^a), such as the mother's education and age, and the child's race, gender and birth weight. Formally:

$$ln(A_0) = X_0^a \alpha_0^x + \eta_0^a \tag{5}$$

where α_0^x picks up the idea that in-utero investments and children's genetic endowments differ by family types.

3.2 Maternal Investment Decisions

As described in the previous section, the child's cognition is determined by mother's time (MT_t) and goods (G_t) investments. These investments are determined by the mother's time allocation decisions. That is, in every period, the mother rationally chooses the amount of hours to spend in the labor market and the amount of hours to spend with the child in the form of time investments. She takes into account how these decisions affect her own and the child's human capital accumulation. By working more hours, the mother accumulates labor market experience, which will influence her future earnings potential. Similarly, by spending quality time with her child she improves the child's human capital stock. Her decision depends on both her preferences and constraints.

3.2.1 Preferences

In every period t, the mother chooses $d_t = (HW_t, MT_t)$, where HW_t represents the choice for annual hours of work and MT_t represents the choice for hours engaged with the child in cognitive productive activities. A woman's preferences over the choice set is defined by her period utility function. Her period utility depends on her current mental health status H_t and observed individual characteristics X_t^u. The utility function is separable across consumption (C_t), leisure (L_t) and the child's human capital (A_t).

$$\begin{aligned} U(C_t, L_t, A_t; H_t, X_t^u) = {} & \lambda_c(H_t, X_t^u) \times f_c(C_t) \\ & + \lambda_l(H_t, X_t^u) \times f_l(L_t) \\ & + \lambda_a(H_t, X_t^u) \times f_a(A_t) \end{aligned} \tag{6}$$

The function $\lambda_c(.)$ allows the marginal utility of consumption to vary with the mother's mental health status as well as observable characteristics such as her education and age.

Mental health enters $\lambda_c(.)$ in order to capture the idea that individuals in poor mental health receive different enjoyment from consumption than individuals in a good mental health state. Similarly, mental health enters $\lambda_l(.)$ as a result of the fact that individuals suffering from mental illnesses are more likely to spend time out of the labor market and miss days of work, and thus could have a higher cost of working (Frijters, Johnston, and Shields, 2014). It is less obvious but also possible that mental health could influence how mothers value their children's human capital development $\lambda_a(.)$.

3.2.2 Constraints

The model assumes women face two constraints in every period, a budget constraint and a time constraint. The budget constraint is given by:

$$C_t + G_t = Inc_t = w_t \times HW_t + N_t + B(\tau_{st}, w_t, HW_t, N_t) \tag{7}$$

where G_t corresponds to the income share that is spent on the child as goods investments, Inc_t is the total family income, N_t is the part of income that does not depend on the woman's labor supply and includes for example the husband's labor income if the woman is married, family transfers and gifts, and $B(\tau_t, w_t, HW_t, N_t)$ are government transfers received by the family such as food stamps, welfare benefits and earned income tax credits. Government transfers are assumed to depend on state-year welfare rule parameters τ_{st}, the wage rate w_t, hours of work HW_t and other family income N_t. [14] [15] [16]

One assumption that is commonly made in the literature and that I follow here is that all families spend an equal and fixed proportion of their income on their child in the form of goods investments. That is, $G_t = a \times Inc_t$. This assumption is necessary since many goods investments, such as the quality of the child's toys, the number of books she has access to and whether she has access to a computer, are usually unobserved or hard to quantify monetarily.

[14] As was noted by Moffitt (1983), many women who are eligible for welfare benefits based on their income do not collect them. The model explicitly ignores the welfare participation decision. This is to keep the model simple and tractable.

[15] It is important to note that these welfare rules should affect individuals differently depending on their previous welfare participation. For example, work requirements might be binding for some individuals but not for others depending on the age of their youngest child and on their previous labor force and welfare participation. The model ignores these important dynamics.

[16] Welfare rule parameters (τ_{st}) provide important exclusion restrictions as they influence the woman's decisions but do not affect her labor market productivity directly and only enter the child's human capital production function through the family income. I explain this identification argument in more detail in Section 4.3.

The time constraint is given by:

$$L_t = TT - HW_t - MT_t \tag{8}$$

where TT is the total time available for the women in a year and leisure will depend on how many hours are left after taking into account the number of hours spent in the labor market and the number of hours spent interacting with the child.

3.2.3 The Wage Process

The mother's labor market productivity determines the budget constraint she faces as well as the amount of monetary resources to be invested in the child for any given time allocation decision. As a result, both goods and time investments received by the child should depend on the mother's labor market productivity.

The wage process takes into account the women human capital accumulation through work experience, or learning by doing. The wage offer at each period is assumed to be determined by the woman's observable characteristics (X_t^w), which include her age, race and education. It is also assumed to depend on her experience stock at the beginning of the period (EX_t) , her employment decision in the previous period (HW_{t-1}), her mental health state in the current period (H_t) and local labor market conditions (ζ_{st}) in her state of residency (s). That is:

$$ln(w_t) = X_t^w \beta_x^w + \beta_1 H_t + \beta_2 EX_t + \beta_3 \mathbb{1}[HW_{t-1} = 0] + \zeta_{st}\beta_s^w + \eta_t^w \tag{9}$$

where β_x^w allows the model to capture returns to education and possible labor market discrimination based on the woman's race, and β_1 captures the idea that mental health disorders are associated with a loss in productivity in the labor market, leading to lower wages and a higher probability of being unemployed (Ettner, Frank, and Kessler, 1997). The third term in Equation 9 captures the labor market returns to human capital accumulation through work experience, and β_3 captures the temporary labor market penalty for spending time out of the labor market. That is, the dynamic wage process allows for endogenous state dependence through human capital accumulation and the dependence of the current wage offer on the woman's previous work choice. β_s^w is a vector that translates labor market conditions (ζ_{st}) into offered wages. [17] Work experience accumulation is determined by the following

[17] State variation in labor market conditions (ζ_{st}) are important for the identification of the empirical model described in Section 4.

process: $EX_{t+1} = EX_t + HW_t$.

3.2.4 Value Functions

The solution for the mother's time allocation decision can be derived from the value functions implied by the model. That is, let Ω_t be the state space faced by the mother that arises from her decisions made up to period t then the mother's optimal time allocation choice in period t is given by:

$$\{HW_t, MT_t\} = \arg\max\{V_t(\Omega_t)^1, ...V_t(\Omega_t)^J\}$$

Where the utility of choice j for individual i at any period is given by:

$$V_t(\Omega_t)^j = U_t^j(C_t, L_t, A_t|d_t = j, \Omega_t) + \beta\mathbb{E}[V_{t+1}(\Omega_{t+1})|d_t = j, \Omega_t]$$

where her choice ($d_t = \{HW_t, MT_t\}$) will depend on the state space she faces in period t (Ω_t) as well as on her beliefs on the state space evolution given her choices $\mathbb{E}[\Omega_{it+1}|d_t = j, \Omega_t]$.

This is a good time to mention one more time that I will not structurally solve for these value functions, as explained at the beginning of this section. Instead, in my empirical model, I approximate the maternal time allocation decision with linear-in-parameters policy functions. Following the structure of the value functions, these policy functions will depend on all variables in the state space at time t. The approach is described in more detail in Section 4.1.

3.3 Mental Health Mechanisms

The relationship between maternal mental health and child cognitive development can be represented through five key mechanisms. I discuss these different pathways below.

The first mechanism corresponds to the direct effect of maternal mental health on children's human capital accumulation. This mechanism is captured by α_{4t} in Equation 4. The direct mechanism can be thought as the effect maternal mental health has on children that is not captured by the other channels. Theoretically, one possible explanation is contagion of mental health, where children suffer from their parents' psychological distress and in turn develop psychological problems of their own (Rosenquist, Fowler, and Christakis, 2011; Eisenberg et al., 2013; Ross, 2000). Higher stress inhibits planning, emotional control and attention, and as a result can lead to cognitive developmental problems (Blair, 2010; Blair et al., 2011). This channel also has dynamic implications. First, parents might increase investments in their child in the current period as a way to compensate for this decrease in human capital. Second, due to dynamic complementarity, a decrease in current human capital could affect the returns of family investments in subsequent periods.

The second mechanism corresponds to the effect mental health has on the productivity of maternal time investments. That is, this third mechanism is related to a change in the quality of these investments. This idea comes from the family stress model in sociology, and suggests that a distressed mother can lose her ability to be supportive and to interact in a consistent manner with her child. This decrease in quality of mother-child interactions results, in turn, in fewer learning experiences for the child (McLoyd, 1990; Mayer, 2002). The model captures this channel with the parameter α_{10t} in Equation 4. This parameter captures the degree of complementarity between maternal mental health and maternal time investments, and as a result, captures how the returns to maternal time investments change with the mother's mental health status. A high degree of complementarity between these two inputs implies that the value of maternal time investments is much higher for mothers in good mental health when compared to those in poor mental health. [18]

The effect mental health on the value of leisure leads to two other mechanisms. That is, the effect of maternal mental health on the quantity of maternal time investments and on her labor force participation. In the model, this effect is described by the marginal utility parameter $\lambda_l(H_t, X_t^u)$ in Equation 6. The idea is that mental health problems can influence impulse, attention and emotional control, so that spending consistent time in productive activities, such as time in the labor market or engaged with the child, becomes more costly (Blair, 2010; Frijters, Johnston, and Shields, 2014). This increase in cost is captured by an increase in the marginal utility of leisure and will result in a reduction in investments in the child. An increase in leisure implies either a decrease in monetary investments due to lower labor force participation or a decrease in time investments. A reduction in labor force participation will also reduce the mother's human capital accumulation. [19]

These reductions in the woman and her child's human capital also have dynamic implications. A decrease in the mother's experience capital can lead to a decrease in her future labor market productivity, as captured by β_2 in Equation 9. This, in turn, leads to lower resources available in the future to be invested in the child. Similarly, a decrease in the child's human capital will influence the returns of future family investments. This comes from the idea of dynamic complementarity, where the returns of current investments depend

[18] The same could be true about the complementarity between maternal mental health and family income. It is possible that financial investments in the child are more productive for mothers in good health. This would be captured by α_{9t} in Equation 4.

[19] Similarly, mental health can affect the value the mother places on consumption (λ_c) and on the child's human capital development (λ_a), also influencing her investment decisions.

on the amount of past investments received by the child (see Aizer and Cunha (2012) and the discussion in Section 3.1).

The fifth and last mechanism corresponds to the mental health effect on the mother's productivity in the labor market (Ettner, Frank, and Kessler, 1997). This effect is captured by β_1 in Equation 9. A reduction in the mother's labor market productivity, conditional on hours worked, implies a reduction in resources to be invested the child. This mechanism is especially important for single women, who are the sole bread-winner in the household. This channel also has dynamic implications due to an ambiguous effect on the mother's labor force participation.

4 Empirical Strategy

This Section describes the estimation strategy used in the paper. I start by describing how I approximate mothers' time allocation decision rules with policy functions. I also discuss the benefits and costs of this approach. I then move to explore the main threats to estimation - measurement error and endogeneity of inputs - and how I handle these issues. At the end of the section, I describe the method of simulated moments (MSM) procedure that I use to estimate the empirical model.

4.1 Approximation to the Decision Rules

The empirical strategy involves approximating maternal time allocation decisions with policy functions and estimating these jointly with the child's technology of skill formation and the mother's wage offer. This approach is similar to that of other papers in the literature (see (Cunha, Heckman, and Schennach, 2010) and (Agostinelli and Wiswall, 2016) for two examples). The alternative approach would be to fully estimate the dynamic model described in the previous section. That would allow me to estimate the preferences parameters described in Equation 6. However, it would be computationally burdensome and would require me to make explicit assumptions regarding the mother's knowledge of her child's skills and of the technology of skill formation. Moreover, it would require me to make strong assumptions regarding maternal investments in other children in the household, or to restrict my sample to single child families.

As explained in Section 3.2.4, the mother's choices in time t ($d_t = \{HW_t, MT_t\}$) will depend on the whole state space she faces in period t (Ω_t) and on her beliefs on the state space evolution given her choices $\mathbb{E}[\Omega_{it+1}|d_t = j, \Omega_t]$. The specific form of the policy functions for the mother's time allocation decision will depend on how one specify the mother's preferences as well as the mother's knowledge about both her child's ability and the technology of cognitive skill formation. However, without taking a stance on these issues, we could write the policy functions for the mother's time allocation as a general function of the state space faced by the mother in period t. This approach accommodates most models of maternal behavior. That is, we can write the policy functions for the mother's time allocation decisions as:

$$HW_t = f^{hw}(\Omega_t) + \eta_t^{hw} \tag{10}$$

$$MT_t = f^{mt}(\Omega_t) + \eta_t^{mt} \tag{11}$$

where η_t^{hw} and η_t^{mt} capture shocks to the mother's decision.

This estimation approach proposed has some clear advantages and disadvantages. There are three main advantages. First, it is a simple and tractable approach that avoids the computational burden of estimating a fully structural model of maternal choices. Second, it avoids making strong assumptions about the investment process and can approximate multiple models of household behavior. For example, it avoids making assumptions on the mother's knowledge about the technology of skill production. [20] These assumptions can heavily influence policy simulation exercises. Third, it allows me to estimate the model for households with multiple children by allowing the mother's decisions to depend linearly on the family composition. This is not possible on a fully structural model. As a matter of fact, since allocation of investments across all children in a household is rarely observed in data, most papers that try to recover individual preferences have focused on one-child families (see Bernal (2008); Griffen (2012); Brilli (2014) for examples). [21]

The main disadvantage of the proposed empirical strategy is that it does not allow me to recover deep utility parameters from the model (Equation 6). This can be problematic in counterfactual policy analysis as I cannot estimate the effect of policies on mothers' preferences. Moreover, it does not allow me to estimate the effect of the mother's mental health on the these preferences. For example, the overall effect of mental health on labor force participation in Equation 10 captures both the effects of mental health on the marginal value of leisure and consumption as well as its effects on the mother's wages and the child's cognition, and how these affect the mother's labor force participation.

[20] As a matter of fact, Cunha, Elo, and Culhane (2013) provides evidence that mothers have biased beliefs about the production function of child skills.

[21] One exception is Del Boca, Flinn, and Wiswall (2014) which allows for both one-child and two-child families.

4.1.1 Linear Policy Functions

Ideally I would like to estimate the policy functions nonparametrically as shown in Equations 10 and 11. However, given the large state space, large number of parameters (100+) and the number of observations ($\sim 2,500$), for computational and identification reasons, I decided to assume the policy functions are linear-in-parameters.

The state space is composed by many different variables described in the conceptual model. There are three state variables that evolve endogenously in the model: labor market experience (EX_{it}), the history of hours in the labor market ($\{HW_{iz}\}_{z=0}^{t}$) and the history of maternal time investments ($\{MT_{iz}\}_{z=0}^{t}$). These variables determine the wage offer received by the mother and the child's ability in period t (see Equations 4 and 9). There are also exogenous state variables that are fixed over time or evolve exogenously from the model. These include exogenous variables that determine the child's initial ability (X_{i0}^{a}), exogenous variables that determine the wage offer (X_{it}^{w}), exogenous variables that enter the flow utility function (X_{it}^{u}) and the mother's mental health (H_{it}), see Equations 5, 9 and 6. Moreover, it includes state level variation in welfare rules (τ_{st}) and state variation in labor market conditions (ζ_{st}) that determine family income and hourly wages. The state space can be characterized by: $\Omega_{it} = \{EX_{it}, \{MT_{iz}\}_{z=0}^{t}, \{HW_{iz}\}_{z=0}^{t}, \chi_{it}\}$, where $\chi_{it} = \{H_{it}, X_{it}^{w}, X_{i0}^{a}, X_{it}^{u}, \zeta_{st}, \tau_{st}\}$ is the vector of exogenous state variables.

As a result, the linear-in-parameters policy functions for the mother's time allocation decision can be described by: [22]

$$\begin{aligned}
HW_{it}^{*} =& \gamma_0^h + \gamma_1^h EX_{it} + \gamma_2^h \mathbb{1}[HW_{it-1} = 0] + \gamma_3^h HW_{it-1} + \gamma_4^h MT_{it-1} \\
&+ \gamma_5^h H_{it} + X_{it}^{w}\gamma_{xw}^{h} + X_{i0}^{a}\gamma_{xa}^{h} + X_{it}^{u}\gamma_{xu}^{h} \\
&+ \zeta_{st}\gamma_6^h + \tau_{st}\gamma_7^h + \eta_{it}^{hw} \\
HW_{it} =& \begin{cases} HW_{it}^{*} & \text{if} \quad HW_{it}^{*} \geqslant 0 \\ 0 & \text{if} \quad HW_{it}^{*} < 0 \end{cases}
\end{aligned} \tag{12}$$

where η_{it}^{hw} captures shocks to the mother's decision. The policy function for maternal time investments is assumed to follow the exact same structure.

[22] In order to specify the expectation over the evolution of the state variables, these approach needs two assumptions. First, I assume that the mother's decision in the previous period ($\{HW_{it-1}, MT_{it-1}\}$) is a sufficient statistic for the whole history of decisions up to the last period ($\{HW_{iz}, MT_{iz}\}_{z=0}^{t}$). This is required for tractability. Otherwise, I would have to re-write the child human capital production function so as to reduce the state space (see (Bernal and Keane, 2010) as an example). Second, I assume that current state level variables ($\{\zeta_{st}, \tau_{st}\}$) are sufficient statistics for future changes in state level conditions.

4.2 Empirical Model

The empirical strategy constitutes estimating the policy functions described above jointly with the child's technology of skill formation and the mother's wage offer. As a result, the empirical framework can be summarized by the following system of equations:

$$
\begin{aligned}
ln(A_{it+1}) &= ln(K_t) + \alpha_{1t} ln(A_{it}) + \alpha_{2t} ln(G_{it}) + \alpha_{3t} ln(MT_{it}) + \alpha_{4t} ln(H_{it}) \\
&\quad + \ldots + \alpha_{7t} ln(A_{it}) \times ln(H_{it}) + \ldots + \alpha_{9t} ln(G_{it}) \times ln(H_{it}) \\
&\quad + \alpha_{10t} ln(MT_{it}) \times ln(H_{it}) + \eta_{it}^{a} \\
ln(w_{it}) &= \ldots + \beta_1 H_{it} + \ldots + \zeta_{st}\beta_s^{w} + \eta_{it}^{w} \\
HW_{it}^{*} &= \ldots + \gamma_5^{h} H_{it} + \zeta_{st}\gamma_6^{h} + \tau_{st}\gamma_7^{h} + \eta_{it}^{hw} \\
MT_{it}^{*} &= \ldots + \gamma_5^{m} H_{it} + \zeta_{st}\gamma_6^{m} + \tau_{st}\gamma_7^{m} + \eta_{it}^{mt}
\end{aligned} \tag{13}
$$

where the equations have been abbreviated for a clear exposition. Goods investments are assumed to be determined by a fixed proportion of family income ($G_{it} = a \times Inc_{it}$), and as a result I substitute family income for goods investments in the empirical model. Moreover, family income is assumed to be determined by: $Inc_{it} = HW_{it} \times w_{it} + N_{it} + B_{it}$, where Inc_t is the total family income, N_{it} is the part of income that does not depend on the woman's labor supply and B_{it} are government transfers received by the family.

This empirical model allows me to capture most of the mechanisms described in Section 3.3. α_{4t} captures the direct effect the mother's mental health has on children. One explanation is that it picks up contagion of mental illnesses (Rosenquist, Fowler, and Christakis, 2011). The effect of mental health on the productivity of maternal time investments is captured by the complementarity parameter α_{10t}. Similarly, α_{7t} and α_{9t} captures possible complementarities between the mother's mental health and the child's skill and family income respectively. Moreover, β_1 captures the effect mental health has on labor market productivity, as discussed in Section 3.2.3. All these parameters are capturing the deep parameters in the model — the structural effects of mental health.

On the other hand, γ_5^h and γ_5^m are 'reduced form' parameters. These capture the overall effect of the mother's mental health on her labor supply and time investment decisions. These parameters are reduced form because they capture multiple effects. They capture the effect mental health has on the marginal utility of leisure and consumption (λs in Equation 6), as well as the 'indirect' effect through its effect on the wage offer and on the child's ability, and how these affect her time allocation decision.

4.3 Endogeneity and Identification

One important issue for estimation is the endogeneity of investments in the production of children's cognitive skills. So far I have avoided any discussion about endogeneity and identification. In this section, I discuss the source of the endogeneity — unobserved investments — and how I address this issue — using time invariant family types and exclusion restrictions.

The main source of endogeneity has to do with unobserved investments. I allow family income, the mother's time and the mother's mental health to influence the technology of cognitive skill formation. By doing so I ignored many other investments that have been shown to be important for children's development. For example, children differ in whether they attended preschool and in the quality of instruction they receive in school (preschool and compulsory). These investments are key for children's development and are ignored in the technology of skill production in this paper (assuming they are not picked up by family income). Moreover, these schooling investments are correlated with both family income and maternal time investments. For example, mothers spend less time with children that attend preschool. Similarly, I have ignored investments made by the father of the child (e.g. the father's time with the child). Again, it is possible that fathers compensate by spending more time with the child when the mother is absent or is suffering from a mental health condition.

Another endogeneity problem arises when estimating the effect of mental health on the mother's time allocation and on her productivity in the labor market. Here, I worry about reverse causation. For example, just as poor mental health can lead to lower labor market productivity, lower wages can lead to financial strain and higher mental health problems (Dohrenwend et al., 1992).

I control for the endogeneity of mental health in two ways. First, I model the correlation in unobserved shocks across equations with time invariant family types. Second, I use exclusion restrictions derived from the model to identify the causal effect of the mother's mental health, family income, and maternal time investments in children.

4.3.1 Mental Health Function

In order to control for the endogeneity of mental health, I need to specify how mental health is determined. I assume a reduced form specification for the mother's mental health. That is, I assume the mental health function is a log-linear function of the mother observed characteristics and state variation in mental health parity laws, which are described in detail in Section 4.3.3.

Despite a large literature describing the production function of physical health, there is surprisingly very little work in economics discussing the production function of mental health. Psychologists describe that psychological distress, and mental health illnesses in general, develop from the inability of the individual to cope effectively with stressors and emotional turmoil (Horwitz, 2007; Ridner, 2004; Drapeau, Marchand, and Beaulieu-Prévost, 2011). As a result, mental health can be thought as a function of these different stressors as well as protective factors. Some stressors are economic in nature, and as such are considered to be endogenous, such as poverty and economic strain (Conger et al., 1994, 2002). Other are not, and are usually thought to be exogenous, such as the death of a relative (Persson and Rossin-Slater, 2014), or exposure to stressful events such as terrorist attacks (Camacho, 2008).

Protective factors can be thought as conditions that help the individual cope with the stressful event. For example, Evans and Garthwaite (2014) shows that government programs such as the EITC, which is thought to alleviate financial strain, can lead to improvements in maternal depression. Moreover, access to mental health services in the form of therapy and medication can alleviate and treat the symptoms related to mental disorders. In general, policies that improve the access to mental health services are expected to lead to improvements in mental health.

Following these ideas, I assume, psychological distress is a function of the mother's observable characteristics, such as her education and marriage status, as well as the state level variation in mental health parity laws. Observable characteristics capture the fact that certain groups are more likely to be exposed to stressful events than others. Similarly, it captures the idea that certain social groups have more resources to cope with stress than others (Drapeau, Marchand, and Beaulieu-Prévost, 2011). On the other hand, parity laws capture variation in access and coverage to mental health services across states. These services can be thought as helping the mother cope with the different stressors. Formally, the mental health function can be described by:

$$ln(H_{it}) = X_{it}^h \delta_x + \omega_{st}\delta_s + \eta_{it}^{mh} \tag{14}$$

where X_{it}^h are observable characteristics of the mother, ω_{st} is a dummy for whether state s has passed a mental health parity law by year t and η_{it}^{mh} is a shock to the mother's psychological distress.

4.3.2 Unobserved Types

In order to control for the endogeneity of investments, I allow for the unobserved shocks (η_{it}^{mh}, η_{it}^{a}, η_{it}^{hw}, η_{it}^{mt} and η_{it}^{w}) to be correlated across equations. I assume these unobserved shocks have two components: a time invariant component that is common to all shocks, and a time variant component that is assumed to be independently distributed over time and across equations.

These time invariant family types capture the idea that families differ in similar but unobservable ways. For example, it is possible that some families are more likely to send their children to preschool (unobservable in the model), and as a result these children develop at a fast pace even though we observe that they faced lower mother-child interactions. The time-invariant types are assumed to capture these important unobserved differences across families and as a result allow me to model the endogeneity in the empirical model.

Formally, I assume each unobserved shock (η_{it}) has two components. One that is time-invariant and common to all shocks (κ_i) and another that is independent and identically distributed over time and across equations (ϵ_{it}). I further assume that the time invariant component (κ_i) follows a discrete distribution with K types, so that we can write the unobservable shocks as:

$$\eta_{it}^{J} = \sum_{l=2}^{K} \rho_l^J \mathbb{1}[\kappa_i = l] + \epsilon_{it}^{J} \qquad \forall J \in \{a, hw, mt, w, mh\} \tag{15}$$

Moreover, I allow for the distribution of these different family types to differ across the population. I do so in order to account for differences in in-utero investments and genetic endowments across family types. That is, I allow for the probability of mother i to belong to family type k to be a function of her educational attainment at the time the child is born as well as for her mental health status before the child's birth. The hope is that educational attainment and early mental health conditions capture maternal skills and mental health endowments that are unobservable by the econometrician. Moreover, these endowments are correlated with in-utero investments and genetic endowments transmitted to the child, which are also unobserved.

Formally, the probability that individual i belongs to family group k is given by:

$$\pi_{ik} = \frac{exp(\theta_{0k} + \theta_{1k} S_i + \theta_{2k} D_i)}{1 + \sum_{l=2}^{K} exp(\theta_{0l} + \theta_{1l} S_i + \theta_{2l} D_i)} \qquad \forall k \in 1, ..., K \tag{16}$$

where $\theta_{01} = 0$, $\theta_{11} = 0$ and $\theta_{21} = 0$, S_i correspond to educational attainment of woman's i and D_i is a dummy for whether she experiences depression before age 17.

In theory, the number of family types (K) can be as large as the number of individuals in the sample or as low as one. A piori, there is no theoretical reason to choose one number over another. The usual practice is to increase the number of types sequentially until the probability of a given type becomes "small enough". [23] For example, in my preferred empirical specification, I assume there are three family types since the estimated probability of belonging to the forth type was small (< 0.06) for most individuals when I allowed a forth type. [24]

4.3.3 Exclusion Restrictions

There are three endogenous variables in the model: the mother's mental health, monetary investments measured by family income, and maternal time investments. I use exclusion restrictions to identify their causal effects.

In order to identify the causal effect of the mother's mental health, I use variation in state mental health parity laws. In order to estimate this effect, I need a factor that affects the mother's mental health but does not enter anywhere else in the model. That is, something that does not directly influence her labor market productivity, her time allocation decisions, or child cognitive skills. Finding such variation is not easy and the literature has struggled with this issue. Here, I use variation in mental health care access and coverage across states and over time. This variation comes from mental health parity laws passed by states in the 1990s. These laws are described by ω_{st} in Equation 14. I discuss these laws in more detail below.

In order to estimate the causal effect of family income (goods investments) for children's cognitive development, I use variation in both labor market conditions (ζ_{st}) and welfare rules (τ_{st}). In order to estimate this effect, I need a factor that affects family income but does not influence children's cognitive development directly. Both variation in labor market conditions and welfare rules serve this purpose. Labor market conditions determine the wage offer received by the mother (ζ_{st} in Equation 9), and as a result influence family income indirectly. Variation in welfare rules determine government benefits received by the mother (τ_{st} in Equation 7), and as a result influence family income directly. I use the same variation (labor market conditions and welfare rules) to identify the effect of maternal time investments for children's cognitive development. Both of these variables change the budget constraint faced by the mother, and as a result, influence the mother's time allocation decision (labor supply and time with the child). I describe these variables in more detailed below.

[23] This is arbitrary since it is up for each researcher to decide what number is considered "small enough".

[24] Moreover, when I allowed for a forth type, I did not observe any qualitatively changes in my results.

Mental Health Parity Laws : One long standing feature of the U.S. health system has been the unequal coverage by insurance plans of mental health care in comparison to general medical care. Until recently, with the passage of the Paul Wellstone and Pete Domenici Mental Health Parity and Addiction Equity Act of 2008, [25] federal law provided few restrictions on this disparity. [26] In order to counter this lack of legislation, beginning in the 1970s and more aggressively in the 1990s, states passed a series of mandates requiring employers and insurers to regulate mental health benefits in their offered plans.

These laws varied significantly across states. Some states required insurance plans to provide mental health coverage in all offered plans. Moreover, they required that these benefits, including those for substance abuse, to be equal to the benefits for general physical conditions. This is the strongest type of mental health law that was approved. These laws are considered 'full parity' laws. Other states passed milder versions. Some only required insurance plans to offer mental health care coverage but left the purchase decision to the individual buyer. These laws are generally called 'mandate offering' laws. Other states passed weaker laws requiring parity in benefits only if a mental health plan was offered - 'mandate if offered' laws. Besides these distinctions, there were also significant variation across states on which mental health conditions were covered by the law and whether it excluded some important groups. For example, some laws did not apply to individual plans, while others excluded plans offered by companies with less than 50 employees. This variation in the 'quality' of these laws makes it tricky to separate states into parity and non-parity states.

In order to address this issue, I use information provided by the National Alliance on Mental Illness (NAMI), which separated parity laws into two groups: 'comprehensive' and 'limited' laws. Limited laws excluded some important mental health condition or group from the parity restrictions. Following their definition, I assigned a state as having passed a parity law if they passed a 'comprehensive' full parity or mandate offering law. That is, I define that, at year t, state s has a parity law (ω_{st}) in place if by time t it had passed a 'full parity' or 'mandate offering' law that did not exclude individual or group plans and did not excluded important mental health conditions. [27]

[25] In 2008 Congress passed the Paul Wellstone and Pete Domenici Mental Health Parity and Addiction Equity Act, a law that prohibits financial requirements, treatment limitations and benefits for mental health and substance use disorders to be more restrictive than medical and surgical benefits.

[26] One exception, is a 1996 mandate established by the congress that prohibited discrimination with respect to annual benefit limits on employer plans that chose to offer mental health coverage. However, besides annual limits employers were free to discriminate or not offer any mental health benefits.

[27] In order to construct these laws, I follow information collected by the National Alliance on Mental Illness (NAMI) (see: http://www.kantorlaw.net/documents/articles-and-information/2010-IAEDP/Mental-Illness-State-Mental-Health-Parity-Laws.pdf). Whenever needed, I supplemented this information with re-

I argue that these laws only enter the model through their effect on the mother's mental health status. However, one possible threat to identification would be if these laws also improved access to mental health services for children. In that case, these laws could improve child outcomes directly. I argue this is probably not the case in two ways. First, mental health coverage is less of an issue for children since they generally have higher rates of coverage from Medicaid and the Children's Health Insurance Program (CHIP) since 1997. As an evidence, pediatricians are less likely than other caregivers to report not providing outpatient mental health services because of lack of or inadequate coverage (Cunningham, 2009). Second, previous research provides evidence that state parity laws did not affect the likelihood of a child receiving outpatient mental health services (Barry and Busch, 2008) or receiving needed mental health care (Barry and Busch, 2007). [28] In contrast, previous research does show evidence that parity laws improved utilization of mental health care services in adults (Harris, Carpenter, and Bao, 2006). [29]

Labor Market Conditions : I use two variables to capture variation in labor market conditions. The median wage rate in the state for workers in the service sector and the share of the population in the state that works in the service sector. These variables were measured at the state and year level using data from the current population survey (CPS). These variables are commonly used in the literature as exogenous variation in the wage rate and are described in more detail in Table 4.

A possible threat to identification in using labor market conditions is that they are possibly related to the father's labor supply decision. The fact that they affect the father's wage is not a problem since I control for family income in the model. However, they might also influence the amount of time the father spends with the child, which is treated as an unobservable in the technology of skill production function.

Welfare Rules : I use the large variation in welfare rules across states and over time in the U.S. as exclusion restrictions in the model. Welfare rules have been shown to significantly affect the labor supply of single mothers (Moffitt, 1992). Moreover, these rules have been used in previous work to identify the effect of maternal work decision on child outcomes (Bernal and Keane, 2010, 2011). In this paper, I use state variation in waivers and requirements under the Temporary Aid to Needy Families (TANF) program after 1997 and state variation

sults in Lang (2013) and information provided by the National Conference of State Legislature NCLS (see http://www.ncsl.org/research/health/mental-health-benefits-state-mandates.aspx).

[28]Although there is evidence that these laws reduced children's annual out-of-pocket health care spending exceeding $1,000 (Barry and Busch, 2007).

[29]Another threat to identification would be if these laws were correlated with other state level conditions. For example, these laws could be correlated with state level labor market conditions. I cannot rule out this possibility, however, I find that these laws are only weakly correlated (< 0.2) with other state level conditions I use in this paper, such as state level unemployment rate and welfare rules.

in benefits and income requirements under the Aid to Families with Dependent Children (AFDC) program before 1997. In addition, I supplement these with state and time variation in the shape of the earned income tax credit (EITC) schedule for a family of three. This variation is important as it also affects the labor supply of married women (Eissa and Hoynes, 2006). These variables are described in more detail in Table 4.

One issue with these welfare policies is that there are too many of them (18 variables in total), each having a small effect on women's labor supply decision. This is problematic for estimation as it creates unnecessary computational burden. Preferably, I would like to have a smaller set of variables with a stronger predictive power. In order to do just that, I follow the approach proposed in Bernal and Keane (2011). That is, I summarize the information contained in these 18 variables into two scores via factor analysis. These scores were estimated using the principal factor method and the varimax rotation. These scores have two important properties. First, these factors are linear functions of the original policy variables, and as a result, are also valid exclusion restrictions. Second, these scores have a much stronger predictive power than each policy variable separately.

These rules are commonly used as instruments for maternal investments in children. However, I should still mention possible threats to identification. One important threat is the fact that these laws changed significantly in 1997 with the introduction of the TANF program. However, also in 1997, the federal government introduced the State Children's Health Insurance Program (SCHIP). This program largely expanded health insurance coverage for children, and as a result is arguably correlated with child outcomes. I hope that by using variation in welfare rules from 1983 to 2013 and the variation in the EITC schedule this becomes less of a problem.

4.4 Measurement Error

Another issue that can lead to biased estimates is measurement error. Most concerning for this paper is the measurement error in the mental health construct. The Kessler 6 psychological distress scale used in this paper suffers from both the intrinsic measurement error in these self-reported questionnaires as well as measurement error from aggregating information from different measurements - the scale consists of six different questions. In order to control for this problem, I use an item response theory (IRT) approach.

The Kessler 6 psychological distress scale is composed by 6 questions scored on a scale of five values (0-4). The usual approach in the literature is to sum the answers to the 6 questions to end up with a score ranging from 0 to 24. There are, however, many issues with this simple approach. If we think that each question is measured with some noise and that the variance in the noise is different across questions, then summing up the scores on each question will provide a very unreliable and noisy measure of the underlying mental health.

Moreover, each question provides different information about the underlying psychological distress that it is measuring. There is no reason to believe that a score of 4 in one of the measures imply the same level of psychological distress as a score of 4 in another measure. For example, feeling nervous "all of the time" might indicate something different than feeling restless or fidgety "all of the time". This is evident as the prevalence rates of scores are different across questions. Similarly, we have no reason to believe that different changes in scores within a measure provide the same information about the change in the underlying psychological distress. For example, answering 4 versus 3 might imply a greater increase in psychological distress than answering 2 versus 1 in one of the questions. Summing up the scores, again, ignore these issues.

A better approach, common in the psychological literature, is to use an item response theory (IRT) model to control for the measurement error in the measurements as well as this difference in information across questions. Many different IRT models have been proposed in the literature. Here, I use the grade response model proposed by Samejima (1969), which is appropriate for multidimensional ordinal items. Formally, let $M_{ij} = k$ correspond to the answer to question j by individual i, which can take 5 different values $k = \{0, 1, 2, 3, 4\}$. The IRT model is interested in estimating the probability of observing answer k or higher for question j and individual i given the underlying psychological distress level θ_i. This probability is assumed to be given by:

$$Pr(M_{ij} \geqslant k|\theta_i) = \frac{exp(a_j ln(\theta_i) + b_{jk})}{1 + exp(a_j ln(\theta_i) + b_{jk})} \tag{17}$$

where a_j captures the information value of question j and b_{jk} is the kth cutpoint for question j and is usually understood as the difficulty in answering k or higher in item j. Alternatively, the probability of observing outcome k is given by:

$$Pr(M_{ij} = k|\theta_i) = Pr(M_{ij} \geqslant k|\theta_i) - Pr(M_{ij} \geqslant k+1|\theta_i) \tag{18}$$

where $Pr(M_{ij} \geqslant 0|\theta_i) = 1$ and $Pr(M_{ij} \geqslant 5|\theta_i) = 0$.

I compute these probabilities outside the main model estimation. This part of the model is computed by simulated maximum likelihood. Let k_{ij} be the observed answer to question

j by individual i, then the likelihood for individual i is given by:

$$L_i = \int_{-\infty}^{\infty} \prod_{j=1}^{6} Pr(M_{ij} = k_{ij}|\theta_i, a_j, b_{jk}) f(\theta_i) d\theta_i \tag{19}$$

where $ln(\theta_i)$ is assumed to be normal distributed with mean 0 and variance 1 and the model is estimated by simulated maximum likelihood.

The value of the unobserved psychological distress for each individual is estimated in a second step by the empirical Bayes method. The value is estimated by the empirical mean and is determined by:

$$ln(\hat{\theta_i}) = \int_{-\infty}^{\infty} ln(\theta_i) \frac{\prod_{j=1}^{6} Pr(M_{ij} = k_{ij}|\theta_i, \hat{a_j}, \hat{b_{jk}}) f(\theta_i)}{\int_{-\infty}^{\infty} \prod_{j=1}^{6} Pr(M_{ij} = k_{ij}|\theta_i, \hat{a_j}, \hat{b_{jk}}) f(\theta_i) d\theta_i} d\theta_i \tag{20}$$

where $\hat{a_j}$ and $\hat{b_{jk}}$ are the estimated parameters in the first step and $f(\theta_i)$ is the prior distribution of theta. The estimated $\hat{\theta_i}$ is the main measure for the individual psychological distress scale.

4.5 Estimation: Method of Simulated Moments

I estimate the parameters of the model using the method of simulated moments (MSM). The estimation method follows an iterative process. First, I calculate the moments from the data. Then, given an initial guess of the parameter vector, I simulate 10 paths for each woman and her child. That is, I first simulate the path for the mother's psychological distress for the 17 periods (ages 0-16). Then, I simulate the hours of work and the time investment decisions at each period using the structure described in Section 4. Following that, I simulate the wage offer received by the mother at each period following the structure described in Section 3.2.3, and path for the child's cognitive ability described in Section 3.1. Once I have these, I can calculate the moments from the simulated data and the weighted distance between the sample moments and the simulated moments from the data. The iterative process continues until this distance is minimized.

More formally, let Ω denote the parameter vector, $M_S(\Omega)$ denote the vector of moments from the simulated data and M_O the moments from the observed data. Then, the estimated parameter vector $\hat{\Omega}$ solves the following objective function:

$$\hat{\Omega} = \arg\min_{\Omega} (M_O - M_S(\Omega))' W (M_O - M_S(\Omega)) \tag{21}$$

where W is a symmetric, positive-definite weighting matrix. I construct W to be the inverse of the covariance matrix of M_O estimated by bootstrap with 500 replications. That is, I compute the vector of moments M_O^q for each of the Q resamples from the original N data points, which leads to the following covariance matrix for M_O:

$$W = \left(Q^{-1} \left(M_O^q - Q^{-1} \sum_q M_O^q \right)' \left(M_O^q - Q^{-1} \sum_q M_O^q \right) \right)^{-1} \tag{22}$$

The moments that form M_O and consequently M_S include the mean and standard deviation of the child's cognition for each of the child's age. They also include the mean of the child's cognition by different maternal characteristics such as maternal education. I also include the mean of the child's cognition by different percentile levels of maternal investments five years prior to the estimated cognition. Moreover, I include the mean and standard deviation of maternal work hours, maternal time with the child, observed wages and the mother's psychological distress, as well as the mean of each variable by the percentiles of maternal and the child observed characteristics. I also include the correlations between the observed wage rate, hours worked and the maternal time with the child, correlations between the contemporaneous wage rate and lagged work hours, and between the two contemporaneous time allocation choices and the two lagged time allocation choices.

5 Empirical Results

In this section, I discuss my key empirical findings. I start by describing the main estimation parameters and how these compare with estimates from a static model and a model that does not control for the endogeneity of mental health. These comparisons highlight the importance of controlling for endogeneity and allowing for dynamic effects. Next, I describe the overall effect of maternal psychological distress on children's cognitive development, and the relative importance of each proposed mechanism in explaining this effect. I will argue that maternal mental matters since a 1% increase in maternal distress in all periods results in a 0.17% decrease in children's cognitive scores at age 16. I will also show that the effect of maternal distress on the productivity of maternal investments explains 70% of the effect of maternal mental health on children.

5.1 Human Capital Production Function

Table 8 presents the estimated parameters for the main outcome of interest, the child human capital production function described in Equation 4. The estimates show some interesting patterns. The first evident pattern is that the total factor productivity (K) is about 50 percent higher in the second developmental period than in the first. This suggests that inputs in the production function explain a much larger share of cognitive development in the first period than in the second. This finding is similar to previous research that highlight the higher return of investments early in life (see Heckman and Mosso (2014)). The estimated parameters also show that the relative self-productivity of children's cognitive skills (captured by α_1) is much greater in the second developmental stage than in the first stage. The high self-productivity parameter in the second stage also highlights the importance of investing in children early in the life cycle.

Given these results is perhaps not surprising that I find that the relative productivity of family income (α_2) and maternal time investments (α_3) are significantly higher in the first developmental period than in the second. However, I also find that the productivity (or penalty) for the mother psychological distress (α_4) is similar across both periods. This finding could be explained by the idea that the contagion of mental health does not depend on the child's age. It also underlines possible benefits of mental health interventions at later stages in the child's development.

Parameters α_5, α_6 and α_7 in Table 8 are not significantly different than zero. This implies that my model rejects evidence of dynamic complementarities beyond the what is already implied by the Cobb-Douglas. This result is not that different from other papers in the literature. For instance, Cunha, Heckman, and Schennach (2010) find similar evidence under some specifications. [30] I also do not find evidence of static complementarity between family income and the maternal time investments beyond the one implied by the Cobb-Douglas function (α_8 in Table 8). Moreover, I find economic large but statistically insignificant static complementarity between maternal mental health and family income (α_9 in Table 8). Also, this complementarity has an opposite sign in the two developmental stages.

In contrast, I find a large and significant static complementarity between maternal mental health and maternal time investments in both developmental stages. This is one of the key findings in the paper. It suggests that the returns to maternal time investments are highly dependent on the mother's mental health. It suggests that the value of maternal time investments are very high when the mother is in a good mental health state. Moreover, it

[30] Cunha, Heckman, and Schennach (2010) cannot reject the Cobb-Douglas formulation when they estimate the production function using only cognitive skills.

suggests that the value of maternal time investments can be negative for children of mothers in poor mental health.

5.2 Time Allocation

Tables 10 and 11 present the estimated parameters for the two time allocation decisions as described by Equation 12. As I discussed in Section 2.2, the direction of the effect of maternal psychological distress on the time allocation decisions is uncertain since the estimated linear effect captures many different channels. For instance, it captures the effect of maternal distress on the marginal utility of leisure, which is expected to be positive. It also captures the effect of maternal distress on maternal wages, which in turn changes the budget constraint. Moreover, it captures the effect of maternal distress on the child's human capital, which is part of the woman's utility function. One would expect an increase in the utility of leisure to decrease the time spent in either the labor market or interacting with the child. However, a decrease in her productivity in the labor market could have an ambiguous effect due to substitution and income effects. The same thing is true for a decrease in the productivity of maternal time investments.

My findings point to small and economically insignificant effects for the work decision and a negative but small effects for the maternal time investments decision. For instance, I find that a one standard deviation increase in maternal distress increases labor force participation by only 16 hours per year (see Table 10). As a comparison, in the preliminary analysis, I ignored both endogeneity and dynamic issues and found an effect on labor force participation that was four times larger and of a different sign (column [4] in Table 3). This change in sign is also present in a model that allows for dynamic interactions but ignores the endogeneity of mental health. Parameter estimates for this model can be seen in Table A4 in Appendix A. [31] This results is different than other papers in the literature that have estimated a negative effect of mental health on labor force participation (Frijters, Johnston, and Shields, 2014; Ettner, Frank, and Kessler, 1997). Moreover, they highlight the importance of modeling the dynamics of the mother's labor force participation.

Similarly, I find that a one standard deviation increase in maternal distress decreases maternal time with the child by only 0.06 hours per week (see Table 11). As a comparison, this estimated effect is around ten times smaller than in models that do not control for the endogneity of mental health (see column [2] in Table 3 and results in Table A5).

[31] For the results in Appendix A, I re-estimate my main empirical model under the assumptions that the shocks in each equation are uncorrelated across equations. In other words, I assume that there are no unobserved family types

The remainder results in Tables 10 and 11 are unsurprising. I find that highly educated mothers spend both more time in the labor market and more time with their children. This is a well known result from the child development literature (Kalil, Ryan, and Corey, 2012). I also find that mothers spend more time with girls than boys and that higher non-maternal labor income is related to a lower time spent with the child. Finally, I also find that the two welfare rules factors are significantly predictive of the two time allocation decisions.

5.3 Wage Offer

Table 12 presents the estimated parameters for the hourly wage equation described in Equation 9. According to the intuition described in Section 2.2, one would expect maternal psychological distress to be negative related to the productivity in the labor market. However, I do not find that to be the case once I control for the endogeneity of maternal distress. A one percent increase in psychological distress causes a 0.002 percent decrease in maternal hourly wages, which is economically insignificant.

Before controlling for the endogeneity of mental health the estimated relationship between distress and wages was between ten to twenty times larger. These can be seen in column [6] in Table 3 and in Table A6). Moreover, the estimated results are much smaller than the reported numbers in the rest of the literature (see (Ettner, Frank, and Kessler, 1997) as an example). These results highlight the importance of properly accounting for the selection into employment and for the endogeneity of mental health.

The other parameters in the wage equation follow standard economic theory. I find that maternal years of education is positively related to labor market productivity, that the offered wage increases as the woman ages, and that a stronger labor market, as measured by median service sector wages, is positive related to hourly wages. Moreover, I find a positive relationship between labor market experience and wages and a strong penalty for spending a period outside the labor market.

5.4 Decomposition

When taking in account all of the different mechanisms I find that maternal mental health matters for children's cognitive development. This is one of the key findings in this paper. I find that on average a 30% decrease in mothers' psychological distress result in a 5.09% increase in children's cognitive skills at age 16. This effect is large and similar to, for example, the effect of a $350 per week increase in family income. [32] This effect is reported in the first row of Table 5. This effect can be seen graphically in Figure 5. The solid line plots the simulated change in cognitive scores at age 16 for the median child for different levels of maternal distress.

Two mechanisms are key in explaining the effect of maternal distress on children's development. The most important mechanism is the effect of maternal mental health on the productivity of maternal time and goods investments. I call these 'complementarity effects'. As can be seen in Table 5, this mechanism alone explains about 70% of the overall effect. That is, this mechanism alone implies that a 30% decrease in mothers' psychological distress would result in a 3.72% increase in children's cognitive skill at age 16. [33] [34] The importance of this mechanism can also be seen graphically in Figure 5. Once I control for these complementarities changes in maternal distress have a significant smaller effect on the child's cognition.

The importance of this mechanism is explained by two parameter estimates. First, it is explained by the large negative complementarity between maternal time investments and maternal distress in the technology of cognitive skill formation (α_{10} in Table 8). It is also explained by the finding that maternal distress does not influence the quantity of maternal time investments (see Table 11). These results together, imply that mothers in poor mental health spend the same amount of time engaged with their children, when compared to mothers in good mental health, even though their time investment is significantly less productive (and sometimes harmful) for their children. The fact that some mothers spend time with their children even when it is not productive (or harmful) to do so highlights the benefits of policy interventions.

The second important mechanism is the direct effect of maternal mental health on children's cognitive development (α_4 in Table 8). This mechanism captures all the ways mental health affects children that are not captured by the other mechanisms in my model. For

[32] These results on family income are comparable to other research. For example, using the same data Del Boca, Flinn, and Wiswall (2014) finds that a $250 weekly increase in child goods lead to 4.6% increase in child quality at age 16.

[33] Here is a brief description on how I compute the separate effect of each mechanism. First, I simulate children's cognition scores at age 16 without any changes into the model. Then, I create a new measure for the mother's distress that is 30% smaller. Next, I substitute this new measure for the old one in the maternal labor force participation equation, and compare the new simulated children's cognition scores at age 16 with the old score. This allows me to compute the percentage change in children's scores due to the effect of maternal distress on the mother's labor force participation alone. Then, I allow the new measure of maternal distress to enter the model through the other mechanisms one at a time. This allows me to compute the change in children's scores due to each of the other mechanisms.

[34] The order of the mechanisms can change the estimated contribution of each mechanism. However, the results are very similar independent of the order used.

example, it captures mental health contagion, the idea that the child develops mental health problems of their own by being exposed to the mother's mental health problems. The direct effect explains about 30% of the overall effect, as I describe in Table 5. This mechanism alone implies that a 30% decrease in mothers' psychological distress would result in a 1.38% increase in children's cognitive skill at age 16. I also depicted this mechanism graphically in Figure 5. The relative importance of the direct effect is represented by the second dotted line. It is also important to notice that, differently than family income (α_2) and time investments (α_3), the effect of maternal distress (α_4) is high in both developmental stages. This is also true for the complementarity effect (α_{10}). This means that policies that focus on improving maternal mental health are especially important when targeting older children.

I do not find strong evidence that the other mechanisms play an important role for children's cognitive development. These other mechanisms correspond to the proposed effect of the mother's mental health on her labor force participation, on the time spent with her child, and on her labor market productivity. This is perhaps surprisingly given that I do find evidence of these mechanisms when looking at static effects, as I demonstrated in Section 2.4. However, evidence of these effects disappear once I allow for dynamics in the mothers' labor force participation decision, and, more importantly, when I control for the endogeneity of mental health, as I described in the beginning of this section. These results highlight the importance of constructing a model that allows for dynamic interactions and endogeneity.

6 Policy Analysis

The results discussed in the previous section suggest two avenues for policy intervention. Two mechanisms explain the effect of maternal psychological distress on children's development: the direct effect of maternal distress and the negative complementarity between maternal distress and maternal time investments. Policies that aim to improve the cognitive development of children of at-risk mothers should target these two mechanisms. One would be to treat at-risk mothers for their mental illness. Another policy would be to improve maternal parenting, as in home visitation programs.

6.1 Mental Health Treatment

The most obvious policy intervention would be to screen mothers for psychological problems and treat all mothers at risk of developing a mental illness. This approach is currently recommended by the American Academy of Pediatrics regarding maternal postpartum depression. The Academy recommends that pediatricians screen mothers for postpartum depression at the infant's 1, 2, and 4 month visits (Earls et al., 2010). Similarly, we could screen and treat mothers for mental health problems at later stages in the child's life.

There are many different approaches to treat mental health problems such as distress, depression and anxiety. Two are the most common: anti-depression medication and psychological interventions, such as cognitive behavioral therapy. Both methods have been shown to be important avenues to treat depression and anxiety disorders in adults. For instance, cognitive behavioral therapy has been shown to increase the probability of remission from depression in adults when compared to usual care, and to decrease the levels of depression by up to 1 standard deviation (Churchill et al., 2013). Psychological therapies have also been shown to effectively reduced generalised anxiety disorder in adults (Hunot et al., 2007). Moreover, both antidepressants and psychological interventions have been shown to reduce symptoms and levels of postnatal depression. For instance, mothers treated with antidepressants were between 43% to 79% more likely than those treated with a placebo to show signs of remission from depression (Molyneaux et al., 2014). [35]

Given the similarities between psychological distress and both depression and anxiety disorders, these results suggest that medication and therapy can significantly reduce maternal distress. Moreover, given these results it does not seem unreasonable to assume that mental health treatment could lead to a 30% decrease in the level of psychological distress. I should mention that coming up with a value for the treatment is inevitably arbitrary given that the efficacy of treatment vary with the type of treatment and also across individuals in the population.

Table 6 shows the effect of different policies on children's cognitive scores at age 16. On average, mental health treatment, represented by a 30% decrease in mothers' psychological distress, results in a 5.09% increase in children's cognitive skills at age 16. This effect was computed by re-simulating the model and calculating children's cognitive skills under the 30% reduction in maternal levels of psychological distress. By comparison, an increase in family income by the median TANF benefit, which was $379 per month in 2,000, only increases children's scores by 1.2%. [36] Unsurprisingly, the returns to mental health treatment are larger for children of mothers in poor mental health. This can be seen in Figure 6 that plots average percentage change in children's cognitive scores at age 16 as a result of mental health

[35] Most of these studies focus on Sertraline, which is an antidepressant of the selective serotonin re-uptake inhibitor class.

[36] One important caveat from computing the effect of income transfers is that the model does not allow increases in family income to affect the mother's mental health. Higher family income should lead to better mental health as it alleviates financial strain and increases the resources to be invested in the mother's mental health.

treatment for different percentiles of maternal psychological distress. [37]

We can use a simple back-of-the-envelope calculation to compare the value of mental health treatments to equivalent income transfers. Russell et al. (1999) estimated the average cost of mental health treatment for adults, including outpatient visits and hospitalizations, to be around $1,200 per year. Assuming the 30% decrease in maternal psychological distress, maternal mental health treatment improves children's cognitive scores by 5.09 percentage points, on average. In comparison, a $1,200 permanent annual increase in family income improves children's cognitive socres by mere 0.32 percentage points. These results suggest that, on average, investments in mother's mental health are 16 times more valuable for improving children's cognitive skills than comparable income transfers.

6.2 Improving Maternal Parenting

Another avenue for policy intervention would be to invest in programs that improve mother-child relationships for mothers with high levels of psychological distress, as in for example home visitation programs. In traditional home visitation programs, a nurse or social worker provides educational training to mothers during frequent visits to the family's home. The training focuses on many areas, including parenting skills, maternal health, and infant nutrition. These programs have become increasingly popular and include well know programs, such as the Nurse-Family Partnership (NFP), Healthy Families America, and the Infant Health and Development Program (Howard and Brooks-Gunn, 2009; Ammerman et al., 2010). These programs have been evaluated by control trials, and shown to improve children's achievement in school, decrease children's behavioral problems and reduce criminality during adolescence (Howard and Brooks-Gunn, 2009).

One of the many ways through which these programs improve child outcomes is by improving maternal parenting skills. As a result, one way to model home visitation programs would be to assume they increase the productivity of maternal time investments $\left(\frac{\partial A_{t+1}}{\partial MT_t}\right)$ for mothers in poor mental health. One big issue is deciding on how much these programs improve the productivity of maternal time investments. Since we don't have actual estimates any number will be arbitrary. I argue that a reasonable assumption is to assume these programs lead to a 20% reduction in the gap in productivity of maternal time investments

[37] In Figure 6, the effect of cash transfers are larger for children of mothers in poor mental health. This is surprisingly, since dynamic complementarity implies that the return of family income would be larger for mothers in good mental health. However, I estimated a positive complementarity between family income and maternal distress in the second developmental period (α_9 in Table 8), which explains why I find the opposite result. As a matter of fact, if I look at younger children, where the complementarity parameter α_9 is negative, the effect of cash transfer are much larger for children of mothers in good health.

across mothers. [38]

Another issue with estimating the value of improving the productivity of maternal time investments is that in doing so I am changing structural parameters in the model. Since I did not estimate the mother's preference parameters (Equation 6), I cannot estimate how changes in the productivity of maternal time investments affect the mother's time allocation decisions. As a result, the results in this section rely on the assumption that the reduced form time allocation policy functions remain the same after the introduction of the program.

With that in mind, I find that, on average, a 20% reduction in the gap in productivity of maternal time investments results in a 6.31% increase in children's cognitive skills. This can be seen in Table 6. This effect was computed by re-simulating the model and calculating children's cognitive skills under the 20% reduction in the gap in the value maternal time investments. Again, these can be compared to an increase in family income by the median TANF benefit, which only increases children's scores by 1.2%. Moreover, I find large heterogeneity in the returns of this program across mothers, as can be seen in Figure 6. As expected, the benefit of this policy is negligible for children of mothers with low levels of psychological distress. However, this policy improves skills by as much as 11 percentage points for children of mothers with serious psychological distress. [39]

We can use a simple back-of-the-envelope calculation to compare the value of home visitation programs, insofar as they improve maternal parenting, to equivalent income transfers. Burwick et al. (2014) estimated the average cost of home visitation programs to be $6,583 per family for a 44 week enrollment period. One important questions is whether these programs improve maternal parenting skills in the short or long run. That is, do we need to re-enroll families every year or enrolling them once is enough to improve maternal parenting until the child reaches the end of the developmental period. In the former case we should compare these programs to a $6,583 permanent annual income increase, which improves children's cognitive scores by 1.74 percentage points. In the latter case we should compare these programs to a one-time $6,583 increase in annual income, which at age 5 improves children's cognitive scores at age 16 by mere 0.09 percentage points, on average. With all the caveats already mentioned and assuming home visitation programs lead to a 20% reduction in the

[38] As mentioned, this number comes with many caveats. First, the actual improvement in the productivity of maternal time investments can be very different across programs. Second, the improvement is most likely heterogeneous across mothers. Lastly, as far as I am aware nobody has measure the improvements in the productivity of maternal time investments from home visitation programs.

[39] There is a technical explanation for the difference in heterogeneous effects across the two programs. Mental health treatment decreases the level of maternal distress, which enters the child's technology of skill production in 'log-form'. This is not true for the improvement in parenting policy, which directly alters the α parameters in that function. As a result, a 30% in effect of maternal distress will have a much larger effect for children than a 30% decrease in the level of maternal distress.

gap in productivity of maternal time investments, these results suggest that investments in home visitation programs are between 3-70 times more valuable for improving children's cognitive skills than comparable income transfers.

7 Conclusion

This paper builds on many strands of the child development literature in order to evaluate the different mechanisms that relate maternal mental health to children's cognitive development. In the analysis, I allow maternal mental health to determine the quantity as well as the quality of maternal investments. My model estimates, which were derived using data from the Panel of Study of Income Dynamics, shed light on the importance of mother's mental health for children's development.

Using the parameter estimates from the model, I first show that on average a 1% decrease in maternal psychological distress increases children's cognitive scores by 0.17 percentage points. Moreover, I show that the effect of maternal distress on the productivity (quality) of maternal time investments explains 70% of the effect on children. Next, I investigate policy interventions that can mitigate these effects. I argue that treating mothers for psychological distress could improve children's cognitive scores by 5.09 percentage points, similar to a $350 weekly increase in family income. Similarly, I argue that home visitation programs, which improve maternal parenting behavior, also have large benefits for children and are a viable option when treatment does not work. Moreover, back-of-the envelope calculations show that both policies are much more cost effective at improving child outcomes than income transfers.

These results open up many avenues for future research. In particular, future research should explore the different ways that government programs interact with maternal mental health in producing child outcomes. For example, we now know that increases in the earned income tax credit (EITC) are related to improvements in mothers' mental health (Evans and Garthwaite, 2014). We also know that increases in the EITC are related to improvements in children's outcomes (Dahl and Lochner, 2012). As a result, we can ask whether maternal mental health mediates the effect of EITC on children. Moreover, we now know that maternal mental health changes the productivity of maternal time investments, and as a result, we can ask whether differences in maternal mental health can partially explain the puzzling heterogeneity in the returns to childcare programs (van Huizen and Plantenga, 2015).

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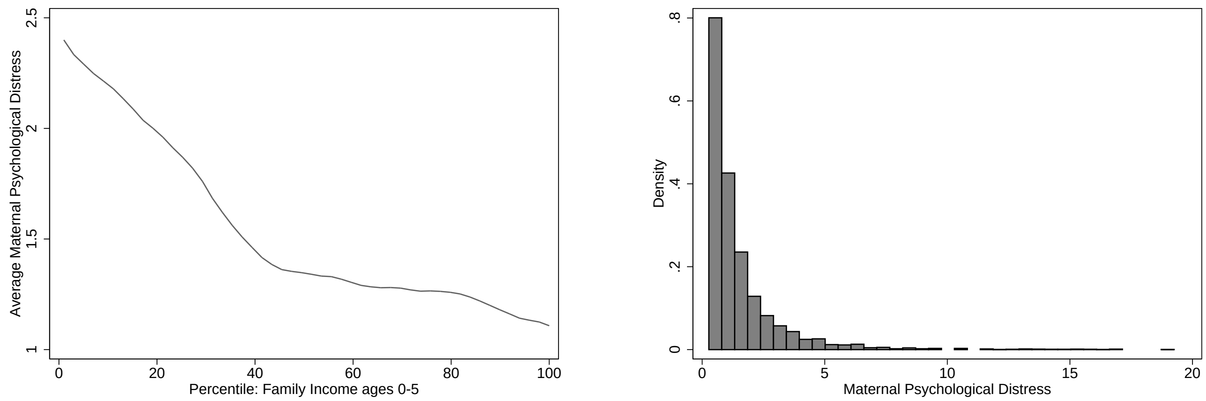
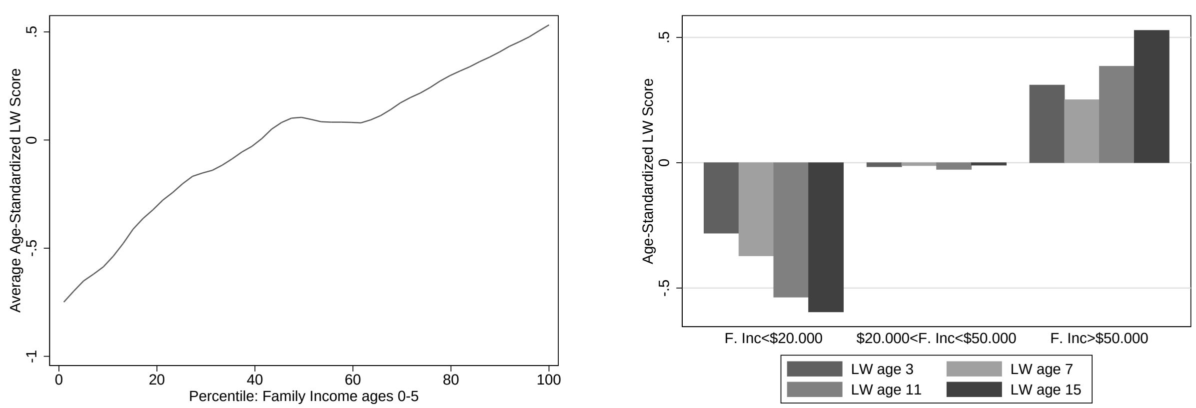
8 Figures



(a) Psych. Distress Scale by Family Income

(b) Psychological Distress Scale - Density

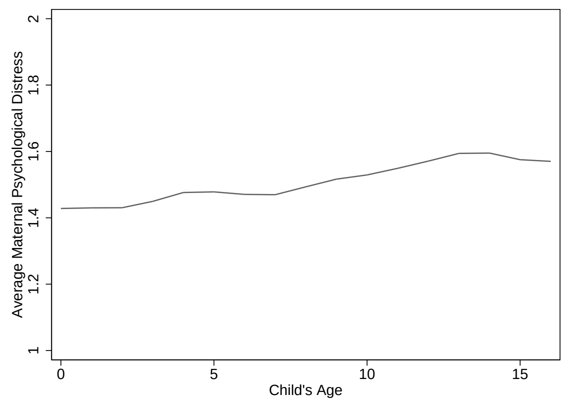
Figure 1: Psychological Distress Scale: Figure 1(a) plots the average distress scale by family income percentiles measured between the ages 0 to 5. Individuals in the lower end of the income distribution are at a much higher risk of developing mental health problems than individuals at the higher end of the distribution. There a sharp drop until the median family income, which is equivalent to $46,000 (measured in 2000 dollars). Figure 1(b) plots the density of the distress scale constructed using Item Response Theory. The responses are concentrated in the left part of the distribution with a long tail.



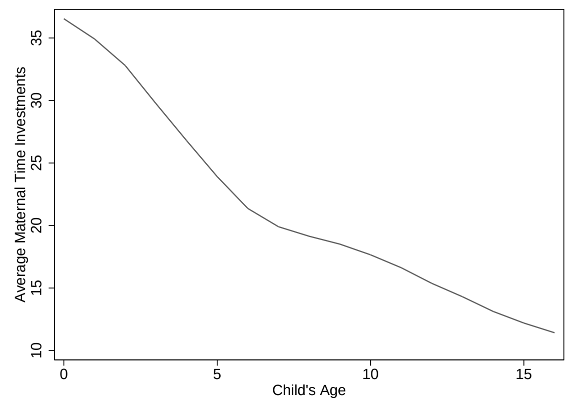
(a) LW Score by Family Income

(b) LW Score by Family Income and Age Groups

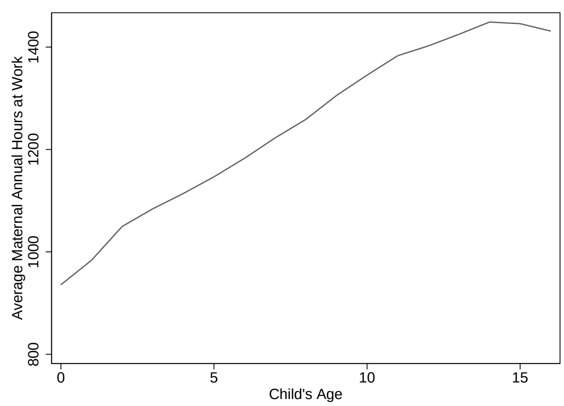
Figure 2: Chidren's Letter-Word Score: Figure 2(a) plots average age-standardized Letter-Word scores by family income percentile. LW score was measured from ages 3 to 16 and family income was measured between the ages 0 to 5. Socioeconomic disparities in children's cognition are large, the cognition gap can be as large as one standard deviation. Figure 2(b) does a similar analysis for different age groups. These socioeconomic disparities are present as early as by age 3 and tend to grow over time.



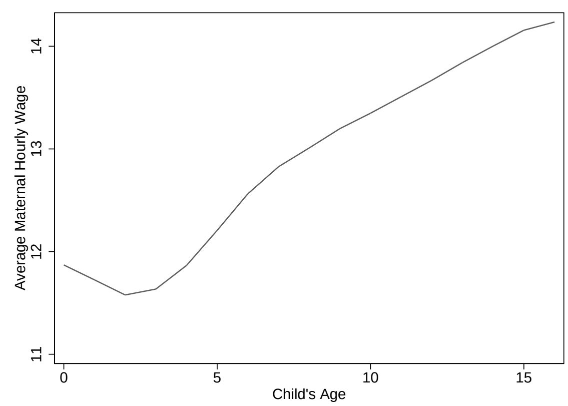
(a) Maternal Distress by the Child's Age



(b) Maternal Time Investments by the Child's Age

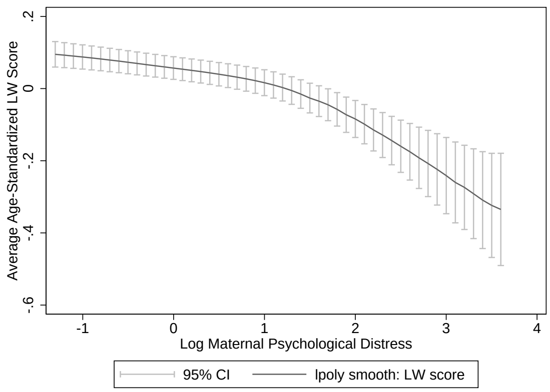


(c) Hours Worked by the Child's Age

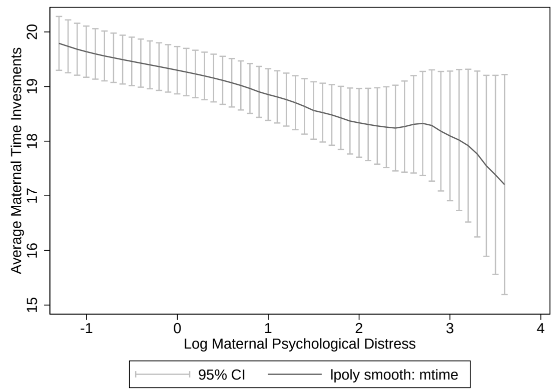


(d) Hourly Wage by the Child's Age

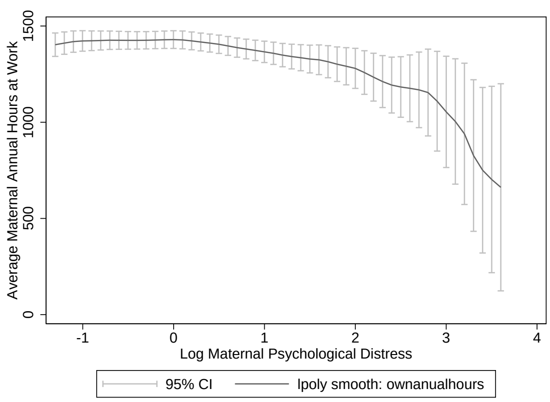
Figure 3: Investments by the Child's Age: These figures plot changes in maternal investments as the child ages. Figure 3(a) plots changes in maternal distress, figure 3(b) plots changes in maternal time investments, figure 3(c) plots changes in the mother's labor force participation and figure 3(d) plots changes in the mother's wage rate.



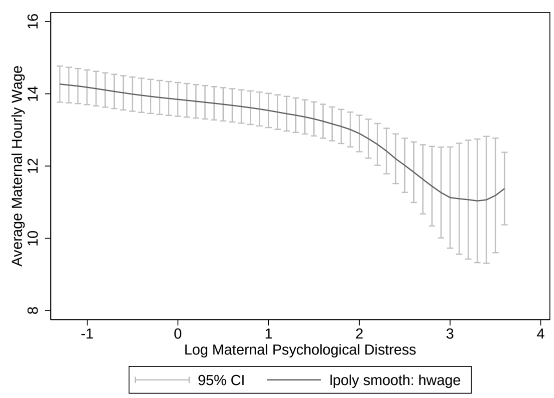
(a) Letter Word Score



(b) Weekly Maternal Time



(c) Annual Hours Worked



(d) Hourly Wage

Figure 4: Outcomes by Maternal Distress: Figures 4(a)-4(d) plot the raw relationship between the maternal distress and children's cognitive skills, maternal time investments, maternal labor force participation, and hourly wage received if employed. 95% confidence intervals are also plotted.

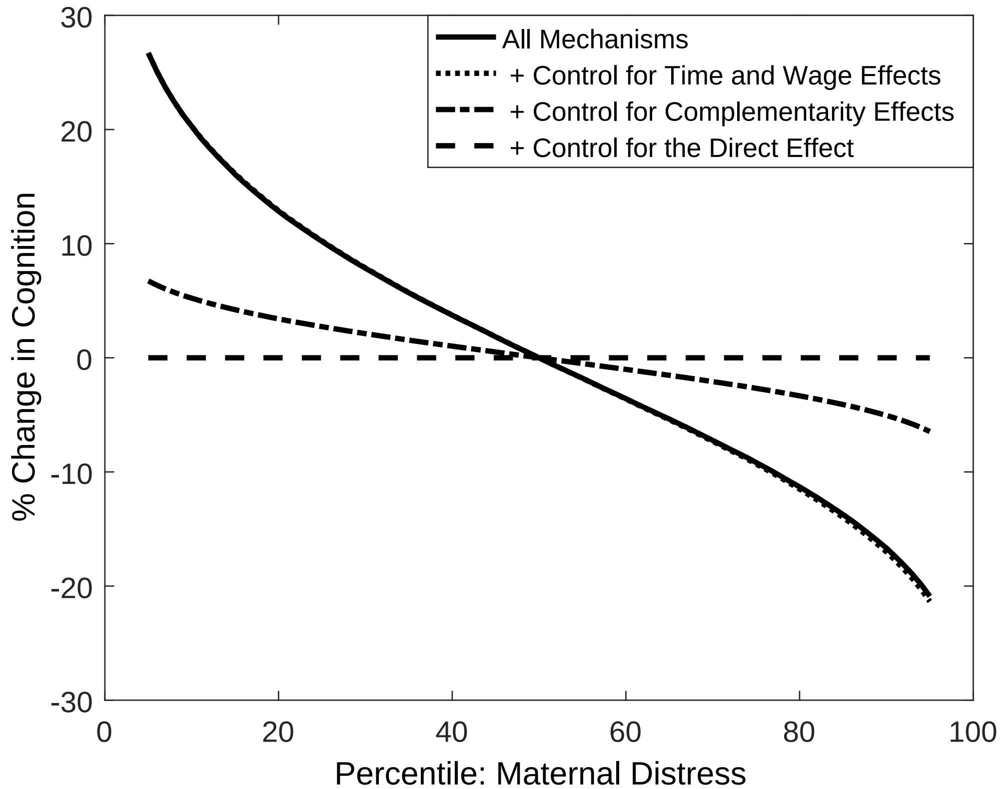


Figure 5: Decomposition of Effect of Maternal Psychological Distress on Child Cognitive Skills: This figure plots the simulated change in child cognitive score at age 16 for the median child for different levels of maternal distress. I re-simulate child cognitive skills under different specifications. That is, I control for different channels through which maternal mental health can affect child outcomes. First, I control for the effect of maternal distress on her labor force participation, time investments and wages. These are very small, so the second curve overlaps with the first. Then, I control for the effect of maternal mental health on the productivity of maternal time investments. Controlling for this mechanism significantly reduces the effect of maternal distress, highlighting its importance. Lastly, I control for the remaining effects. Once I do so, the line becomes flat, as expected.

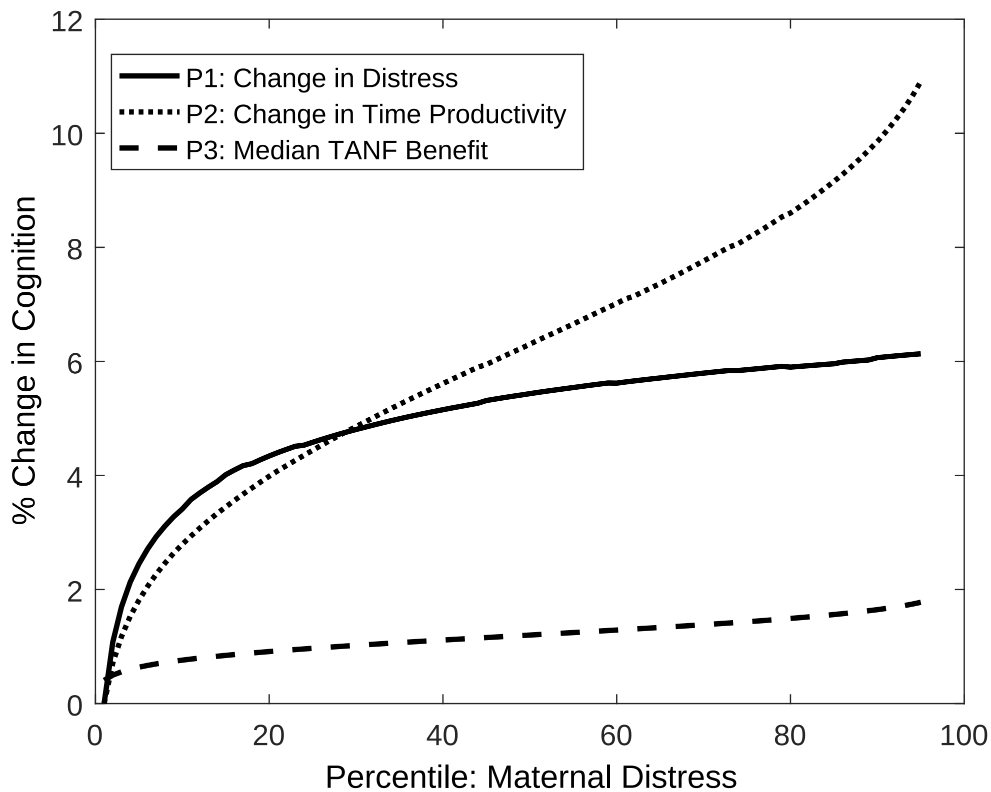


Figure 6: Policies: This figure plots the effect of different policies on children's cognitive development at age 16. These effects are calculated for the median child for different levels of maternal distress. In the first policy, I decrease psychological distress by 30% in the whole population. The second policy, decreases the gap in the returns of maternal time investments across individuals by 20%. Then, I compare these policies to an increase in family income by the median TANF benefit, which was was $379 per month in 2,000.

9 Tables

Table 1: SUMMARY STATISTICS

Variable	Mean	SD	Min	Max	# obs
Child is Female	0.495	0.500	0	1	41803
Child is Black	0.401	0.490	0	1	41803
Mother's Years of Edu.	12.98	1.978	10	17	41803
Mother's Age at Birth	25.68	5.727	13	41	41803
Number of Children	2.791	1.189	1	11	41803
Mother is Single	0.317	0.2165	0	1	41803
Letter-Word Score	1.417	1.093	0.001	12.79	4582
Maternal Distress	1.533	2.066	0.271	36.64	4534
Maternal Time Investments	19.36	14.13	0	77.33	5006
Annual Hours Worked	1209	913.6	0	3640	25795
Hourly Wage	12.76	84.08	1.970	65.80	19864
Mother's Depression B.17	0.043	0.202	0	1	41803
Child-Age Observations					41803

Notes: Summary statistics for the analytic sample of 2,459 children. Children and their mothers were observed over 17 years for a total of 41803 child-age observations. Entries for the child's race and gender and the mother's cohabiting status and depression before age 17 are in the form of percentages divided by 100. Maternal time investments is measured in weekly hours, hours worked in annual hours and hourly wages are in 2000 dollars. The child's letter-word score has been log-age-standardized to have mean 0 and standard deviation equal to 1 at all ages. * denotes the coefficient is significant at the 10% level, ** denotes the coefficient is significant at the 5% level and *** denotes the coefficient is significant at the 1% level.

Table 2: Preliminary: Log Letter-Word Score

Variable	[1]	[2]	[3]	[4]
Log Maternal Distress	-.129***	-.069**	-.068**	-.063**
Log Maternal Time	.	.	.035	.038
Log Family Income	.	.	.	.093**
Controls	(N)	(Y)	(Y)	(Y)

Notes: This table contains parameter estimates from OLS regressions used link maternal investments to child cognitive scores. I regress log age-standardized letter word scores at time $t + 5$ on maternal investments at time t. Controls include the mother's years of education, age at the child's birth, cohabiting status, number of children and the child's race and gender. * denotes the coefficient is significant at the 10% level, ** denotes the coefficient is significant at the 5% level and *** denotes the coefficient is significant at the 1% level.

Table 3: Preliminary: Maternal Investments

	Maternal Time		Annual Hours Worked		Hourly Wages	
	[1]	[2]	[3]	[4]	[4]	[6]
Log Maternal Distress	-.825***	-.547**	-57.662***	-41.810***	-.085***	-.048***
Controls	(N)	(Y)	(N)	(Y)	(N)	(Y)

Notes: This table contains parameter estimates from OLS regressions used link log maternal psychological distress to other maternal investments. I regress weekly maternal time with the child, annual hours worked and hourly wages if employed on log maternal distress. Controls for the time decisions include the mother's years of education, age at the child's birth, cohabiting status, number of children and the child's race and gender. Controls for the wage offer include the mother's age and age squared, her education and state level labor market conditions indicators.

Table 4: STATE LEVEL VARIABLES: DESCRIPTION AND SOURCES

Instruments	Description	Source
	Labor Market Conditions	
$servwage_{st}$	Median hourly wage rate for workers in the Service Sector in State s	MORG
$empservice_{st}$	Share of the employed population working in the Service sector in State s	MORG
	State Variation in TANF Rules	
$DiversionProgram_{st}$	Dummy for whether State s has a Diversion Program in place at Period t	UI-WRD
$JobSearchRequired_{st}$	Dummy for whether State s requires applicants to search for a job before application	UI-WRD
$TPElegible_{st}$	Dummy for whether Two-Parent Families are eligible for benefits in State s	UI-WRD
$TPLimitonHours_{st}$	Dummy for whether State s has a limit on the number of hours a month the principal wage earner can work	UI-WRD
$TPWorkHistory_{st}$	Dummy for whether State s performs a work history test in order to determine eligibility of TP Families	UI-WRD
$TPWaitingPeriod_{st}$	Dummy for whether State s implements waiting periods for TP Families	UI-WRD
$NetIncomeTest_{st}$	Dummy for whether State s performs a Net Income Test before determining eligibility	UI-WRD
$EIDpercent_{st}$	Percent amount of Income disregarded in determining net income for the income eligibility tests n State s	UI-WRD
$EIDflat_{st}$	Flat amount of Income disregarded in determining net income for the income eligibility tests in State s	UI-WRD
$MaxIncEligF3_{st}$	Maximum monthly income for initial eligibility for a family of three in State s	UI-WRD
$MaxBenF3_{st}$	Maximum monthly benefit awarded for a family of three with no income in State s	UI-WRD
$WRHowLong_{st}$	Number of assistance months after which work is required in place in State s "	UI-WRD
$WRYoungCExemption_{st}$	Dummy for whether Stats s exempts the work requirement for a parent caring for a young child	UI-WRD
$WRChildExempt_{st}$	How old (in months) a child can be for the caregiver to be exempt from the work requirement in State s	UI-WRD
$WRNumWExemptions_{st}$	Number of different work exceptions allowed by State s	UI-WRD
$LifetimeTimeLimit_{st}$	Dummy for whether State s has Time Limits in place	UI-WRD
$TLLength_{st}$	Maximum number of assistance months before benefits are terminated in place in State s	UI-WRD
	Other Policy Variables	
$unemp_{st}$	Unemployment Rate in State s	LAUS
$SEITC_{st}$	State earned income tax credit as a percentage from the federal EITC	TAXSIM
$SEITCrefundable_{st}$	Dummy for whether the state EITC is refundable	TAXSIM
$MHparity_{st}$	Dummy for whether the state has passed by time t a comprehensive or mandate offering law.	NAMI & NCLS

Note: LAUS refers to the Local Area Unemployment Statistics data provided by the Bureau of Labor Statistics, MORG refers to the CPS Merged Outgoing Rotation Groups data provided by the National Bureau of Economic Research using data from the Current Population Survey (CPS), UI-WRD refers to the Urban Institute's Welfare Rules Database, TAXSIM refers to the National Bureau of Economic Research's TAXSIM program data on State Earned Income Tax Credits, NAMI refers to the National Alliance on Mental Illness parity laws table, and NCLS the National Conference of State Legislatures mental health benefits state mandates table.

Table 5: MECHANISMS

Mechanism:	%Δ in Cognition	% Contribution
Total Effect	5.09	100.00
Δ in L.F. Participation	-0.06	-1.18
Δ in Time Investments	0.03	0.59
Δ in L.M. Productivity	0.02	0.39
Complementarity of Mental Health	3.72	73.08
Direct Effect	1.38	27.12

Notes: This table describes and decomposes the average effect of a 30% decrease in psychological distress in the overall population on children's cognitive scores at age 16. Column [1] depicts the average percentage change in children's cognitive scores due to each mechanism. Column [2] depicts the percentage contribution of each mechanism for the overall effect. The first mechanism captures the effect of maternal mental health on maternal annual hours worked, the second captures its effect on maternal time investments and the third its effect on maternal wages. The forth mechanism captures the effect of maternal mental health on the return of maternal time investments. The fifth mechanism captures the remaining effect of maternal mental health for children's cognitive development.

Table 6: POLICY SIMULATIONS

Policy:	%Δ in Cognition
30% $\downarrow$ in Distress	5.09
20% $\downarrow$ in Time Prod. Gap	6.31
$\uparrow$ in Income by the Median TANF Benef.	1.20

Notes: This table describes the average effect of three different policies on children's cognitive scores at age 16. That is, I compute the average percentage change in children's cognitive scores as a result of each policy. In the first policy, I decrease psychological distress by 30% in the whole population. The second policy, decreases the gap in the returns of maternal time investments across individuals by 20%. Then, I compare these policies to an increase in family income by the median TANF benefit, which was was $379 per month in 2,000. On average, this program increases children's cognitive scores by 1.2 percentage points.

Table 7: Psychological Distress

Constant	2.012	(0.401)
Years of Education	-0.069	(0.017)
Age	-0.077	(0.003)
Age sqrd.	0.001	(0.000)
Single	0.283	(0.078)
# of Children	0.057	(0.025)
Depressed at 17	0.561	(0.709)
White Dummy	-0.070	(0.049)
Mental Health Parity	-0.031	(0.013)
Unobserved Type 2	-0.002	(0.000)
Unobserved Type 3	-0.119	(0.017)

Notes: This table contains parameter estimates for the mental health function (Equation 14). It relates log maternal psychological distress to maternal observable variables, the state level mental health parity law, and the time-invariant unobservable types. Bootstrap standard errors are reported in parentheses.

Table 8: COGNITION PRODUCTION FUNCTION

	Parameter	First Dev. Stage		Second Dev. Stage	
Total Factor Productivity	K	0.595	(0.017)	0.938	(0.035)
Self Productivity	α_1	0.140	(0.158)	0.484	(0.128)
Log-Family Income	α_2	0.092	(0.001)	0.012	(0.006)
Log Maternal Time Investment	α_3	0.085	(0.005)	0.009	(0.010)
Log Psychological Distress	α_4	-0.037	(0.013)	-0.025	(0.020)
Log-A_{t-1} $\times$ Log-F.Income	α_5	0.001	(0.001)	0.000	(0.001)
Log-A_{t-1} $\times$ Log-M.Time	α_6	0.002	(0.003)	0.004	(0.006)
Log-A_{t-1} $\times$ Log-Distress	α_7	-0.005	(0.008)	-0.002	(0.013)
Log-F.Income $\times$ Log-M.Time	α_8	-0.001	(0.000)	0.000	(0.000)
Log-F.Income $\times$ Log-Distress	α_9	-0.012	(0.010)	0.015	(0.031)
Log-M.Time $\times$ Log-Distress	α_{10}	-0.052	(0.007)	-0.033	(0.014)
Unobserved Type 2	κ_2	0.003	(0.000)	0.003	(0.000)
Unobserved Type 3	κ_3	-0.093	(0.002)	-0.093	(0.002)

Notes: This table contains parameter estimates for the child human capital production function (Equation 4). The translog function relates child cognitive scores to parental investments in the form of maternal time investments,family goods investments measured by family income and the mother's mental health measured by a psychological distress scale. Time-invariant unobservable types control for unobserved investments. Bootstrap standard errors are reported in parentheses.

Table 9: INITIAL CHILD ABILITY

Constant	-1.279	(0.113)
Mother‘s Years of Education	0.044	(0.005)
Mother‘s Age at Child‘s Birth	0.012	(0.002)
Single	-0.001	(0.000)
# of Siblings	-0.037	(0.031)
White Dummy	0.059	(0.042)
Female	0.146	(0.094)
Unobserved Type 2	0.014	(0.000)
Unobserved Type 3	-0.116	(0.008)

Notes: This table contains parameter estimates for the initial child human capital function (Equation 5). Children's initial human capital is assumed to depend on child and mother's observable characteristics as well as time-invariant unobservable types. Bootstrap standard errors are reported in parentheses.

Table 10: Labor Market Participation

Constant	337.679	(59.698)
Years of Education	66.325	(4.465)
Age at Child's Birth	-0.041	(0.025)
Single	-18.249	(10.617)
# of Children	-156.983	(25.552)
White Dummy	335.792	(45.755)
Child is Female	-33.106	(16.214)
Child's Age	53.541	(7.212)
Child's Age sqrd.	-2.033	(0.513)
Log Non-Labor Income	-0.023	(0.015)
Median State Service Wage Rate	-35.855	(6.664)
State % Employed in Serv. Sector	243.108	(72.271)
State Variation in Welfare Rules 1	114.095	(26.980)
State Variation in Welfare Rules 2	-12.459	(8.469)
Child Younger Than 4	-12.587	(7.853)
Psychological Distress	16.951	(9.948)
Not Working Last Period	-1.020	(1.219)
Experience	2.338	(1.850)
Hours Working Last Period	0.469	(0.040)
Hours With the Child Last Period	-4.394	(1.935)
Unobserved Type 2	216.167	(42.910)
Unobserved Type 3	347.630	(35.791)

Notes: This table contains parameter estimates for the approximated decision rule for labor market participation (Equation 12). It relates annual hours of work to all the state variables in the Conceptual model as well as the time-invariant unobservable types. Bootstrap standard errors are reported in parentheses.

Table 11: Weekly Time Investments

Constant	26.799	(6.219)
Years of Education	0.512	(0.385)
Age at Child‘s Birth	-0.016	(0.009)
Single	-3.780	(1.478)
# of Children	0.011	(0.006)
White Dummy	-6.026	(1.317)
Child is Female	2.194	(1.231)
Child‘s Age	-0.556	(0.255)
Child‘s Age sqrd.	0.091	(0.014)
Log Non-Labor Income	-0.589	(0.506)
Median State Service Wage Rate	-2.080	(1.100)
State % Employed in Serv. Sector	18.437	(5.629)
State Variation in Welfare Rules 1	0.019	(0.007)
State Variation in Welfare Rules 2	69.014	(11.989)
Child Younger Than 4	8.887	(2.276)
Psychological Distress	-0.067	(0.031)
Not Working Last Period	0.145	(0.144)
Experience	-0.062	(0.087)
Hours Working Last Period	0.001	(0.000)
Hours With the Child Last Period	-0.061	(0.024)
Unobserved Type 2	2.715	(2.168)
Unobserved Type 3	-3.279	(2.400)

Notes: This table contains parameter estimates for the approximated decision rule for mothers' time investments in their children (Equation 12). It relates weekly maternal active time with children to all the state variables in the Conceptual model as well as the time-invariant unobservable types. Bootstrap standard errors are reported in parentheses.

Table 12: Hourly Wages

Constant	-1.847	(0.285)
Years of Education	0.194	(0.011)
Age	0.018	(0.002)
Age sqrd.	-0.000	(0.000)
Median State Service Wage Rate	0.010	(0.004)
State % Employed in Serv. Sector	1.522	(0.318)
Log Psychological Distress	-0.002	(0.001)
Not Working Last Period	-0.151	(0.188)
Experience	0.001	(0.000)
Unobserved Type 2	0.082	(0.012)
Unobserved Type 3	-0.119	(0.016)

Notes: This table contains parameter estimates for the wage process (Equation 9). It relates log hourly wages to maternal observable variables, state level labor market conditions, and the time-invariant unobservable types. Bootstrap standard errors are reported in parentheses.

Table 13: Type Probabilities

	Unobserved Type 1		Unobserved Type 2	
Constant	-0.004	(0.000)	-0.012	(0.000)
Years of Education	-0.021	(0.000)	-0.002	(0.000)
Depression before 17	-0.010	(0.000)	-0.022	(0.000)

Notes: This table contains parameter estimates for the time probability equation described in Equation 16.

Appendix A Appendix: Results Assuming Exogeneity of Inputs

This section provides parameter estimates for the model when I do not control for the unobservable correlation across the different decisions and outcomes. As a result, the maternal psychological distress is assumed to enter exogenously in the model. The same true about family income and the mother's time with her child, which are assumed to be exogenous in the child human capital production function. The estimates presented in this section serve as comparison for the results presented in the main paper.

Table A1: Psychological Distress

Constant	1.252	(0.146)
Years of Education	-0.041	(0.001)
Age	-0.053	(0.002)
Age sqrd.	0.001	(0.000)
Single	0.175	(0.008)
# of Children	0.051	(0.002)
Depressed at 17	0.449	(0.038)
White Dummy	-0.066	(0.006)
Mental Health Parity	-0.104	(0.008)

Bootstrap standard errors are reported in parentheses.

Table A2: Cognition Production Function

	Parameter	First Dev. Stage		Second Dev. Stage	
Total Factor Productivity	K	0.579	(0.004)	1.019	(0.010)
Self Productivity	α_1	0.243	(0.026)	0.877	(0.074)
Log-Family Income	α_2	0.108	(0.003)	-0.010	(0.000)
Log Maternal Time Investment	α_3	0.072	(0.001)	0.001	(0.003)
Log Psychological Distress	α_4	-0.009	(0.010)	-0.013	(0.011)
Log-A_{t-1} × Log-F.Income	α_5	-0.000	(0.000)	-0.030	(0.010)
Log-A_{t-1} × Log-M.Time	α_6	0.005	(0.002)	0.036	(0.051)
Log-A_{t-1} × Log-Distress	α_7	0.002	(0.000)	-0.014	(0.021)
Log-F.Income × Log-M.Time	α_8	-0.000	(0.000)	0.000	(0.000)
Log-F.Income × Log-Distress	α_9	0.011	(0.005)	-0.009	(0.007)
Log-M.Time × Log-Distress	α_{10}	-0.076	(0.004)	0.002	(0.007)

Bootstrap standard errors are reported in parentheses.

Table A3: Initial Child Ability

Constant	-0.842	(0.393)
Mother's Years of Education	0.001	(0.009)
Mother's Age at Child's Birth	0.013	(0.001)
Single	0.743	(0.128)
# of Siblings	0.064	(0.030)
White Dummy	-0.031	(0.041)
Female	0.136	(0.081)

Bootstrap standard errors are reported in parentheses.

Table A4: Annual Hours Worked

Constant	272.423	(64.679)
Years of Education	76.661	(7.358)
Age at Child's Birth	0.039	(0.030)
Single	-84.558	(36.578)
# of Children	-307.750	(36.632)
White Dummy	421.549	(41.582)
Child is Female	-40.016	(38.192)
Child's Age	31.242	(7.017)
Child's Age sqrd.	-0.543	(0.380)
Log Non-Labor Income	-0.020	(0.015)
Median State Service Wage Rate	-18.494	(7.519)
State % Employed in Serv. Sector	811.018	(58.033)
State Variation in Welfare Rules 1	25.941	(26.690)
State Variation in Welfare Rules 2	-14.711	(19.557)
Child Younger Than 4	-81.770	(26.435)
Psychological Distress	8.963	(15.367)
Not Working Last Period	-0.779	(2.048)
Experience	2.471	(3.106)
Hours Working Last Period	0.394	(0.015)
Hours With the Child Last Period	-4.725	(2.869)

Bootstrap standard errors are reported in parentheses.

Table A5: Weekly Time Investments

Constant	32.774	(6.967)
Years of Education	-0.340	(0.434)
Age at Child‘s Birth	-0.067	(0.065)
Single	-5.192	(1.614)
# of Children	0.059	(0.074)
White Dummy	-4.825	(0.745)
Child is Female	2.297	(0.415)
Child‘s Age	-0.252	(0.287)
Child‘s Age sqrd.	0.074	(0.005)
Log Non-Labor Income	-0.745	(0.574)
Median State Service Wage Rate	-1.599	(0.630)
State % Employed in Serv. Sector	20.420	(7.774)
State Variation in Welfare Rules 1	-2.590	(1.917)
State Variation in Welfare Rules 2	19.946	(8.863)
Child Younger Than 4	3.298	(1.939)
Psychological Distress	-0.654	(0.637)
Not Working Last Period	1.147	(2.263)
Experience	-0.028	(0.020)
Hours Working Last Period	0.001	(0.000)
Hours With the Child Last Period	0.117	(0.050)

Bootstrap standard errors are reported in parentheses.

Table A6: Hourly Wages

Constant	-1.745	(0.325)
Years of Education	0.216	(0.005)
Age	0.016	(0.001)
Age sqrd.	-0.000	(0.000)
Median State Service Wage Rate	0.015	(0.007)
State % Employed in Serv. Sector	1.335	(0.645)
Log Psychological Distress	-0.024	(0.011)
Not Working Last Period	-0.148	(0.472)
Experience	-0.001	(0.001)

Bootstrap standard errors are reported in parentheses.